

**Using remote sensing to estimate the impacts of wattle species on native grass vegetation**

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Sciences, in the School of Agricultural, Earth and Environmental Sciences, University of  
KwaZulu-Natal.

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## ABSTRACT

This study was stimulated by the long standing challenge of the lack of suitable satellite data with optimal temporal, spectral, and spatial resolutions to monitor rangelands. The study, therefore, sought to evaluate the utility of remotely sensed data in estimating the impact of wattle infestation and clearance on native grass species productivity and diversity. The first objective of this study was to investigate the utility of Sentinel 2 Multispectral Imager (MSI) remotely sensed data and Partial Least Squares regression as a cost-effective and quick assessment technique to map above ground biomass (AGB) of native grass growing under different levels of *Acacia baileyana*, *A. dealbata* & *A. mearnsii*, invasion in Matatiele, South Africa. The second objective focused on assessing the impact of wattle invasion on grass species diversity. This was achieved by investigating the utility of Sentinel-2 MSI data in optimally estimating grass Species richness, Shannon Wiener and Simpson's diversity indices at different levels of wattle invasion. In relation to the first objective, the findings of this study showed that Sentinel 2 MSI data derived vegetation indices optimally estimated biomass in relation to standard wavebands. Results also showed that Sentinel 2 MSI data (combination of raw spectral bands and vegetation indices) predicts grass AGB levels of wattle invasion at reasonable accuracies (RMSE = 19.117g/m<sup>2</sup> and R<sup>2</sup> = 0.8268). The most influential variables in estimating biomass across different levels of wattle invasion were red edge based vegetation indices (VIs) and bands 5,6 and 7. With regards to the second objective, this study showed that following restoration, there were no significant difference ( $p > 0.05$ ) between cleared and uninvaded grassland areas. Results also showed that diversity indices were optimally modelled when compared to species richness. However, for all three diversity variables, individual raw spectral bands yielded lower accuracies when compared to vegetation indices. Overall, the most influential spectral variables

were, bands 5 and 6, NDVI computed from bands 6 and Band 3. Results of this study also showed that Shannon Wiener's index better predicted grass species diversity across different levels of wattle invasion in an alpine grassland (RMSE = 0.2145,  $R^2 = 0.6392$ ) in relation to the other diversity indices. This study was able to demonstrate that Sentinel-2 MSI spectral variables have a potential of offering reliable and accurate estimates of grass species diversity in a wattle infested grassland. The study therefore advocates for the utility of remotely sensed data in monitoring grassland degradation and restoration.

## 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 April 2017 to November 2018, under the supervision of Professor Onesimo Mutanga.

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.

Thulile Vundla                      Signed \_\_\_\_\_                      Date \_\_\_\_\_

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

### **Supervisor**

Prof. Onesimo Mutanga                      Signed \_\_\_\_\_                      Date \_\_\_\_\_

## DECLARATION

I, **Thulile Vundla**, 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,
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Signed \_\_\_\_\_

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## **DEDICATION**

For my mother and my grandmother

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# 1. GENERAL INTRODUCTION

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## 1.1. Introduction

Invasive alien plants species (IAPs) are one of the major threats to native vegetation species. This is because they alter the native community ecosystem structure and functioning (Andreu and Vilà 2011, Niphadkar and Nagendra 2016). IAPs result in the loss of native species diversity, they reduce productivity and above ground biomass (AGB), while promoting bush encroachment in grazing land and in some cases they excessively consume surface and ground water resources (Stohlgren et al. 1999, Bradley et al. 2006, Cavaleri and Sack 2010, O'Connor et al. 2014). The negative impacts of IAPs on the natural vegetation are further compounded by

their rapid spread rates (Le Maitre et. al 1996). Of greater concern is the grassland biome, which has less than 1% of its spatial extent under formal protection in South Africa (Reyers et al. 2005). Egoh et al. (2011) further outlined that grasslands are one of the most threatened principal biomes in South Africa. About 35% of grasslands are lost annually to cultivation, urbanisation and mining in South Africa. Meanwhile, the loss of grasslands through IAPs remains largely unknown and initiatives of accounting these losses are still rudimentary (Egoh et al. 2007, Firn et al. 2013). Therefore, the alarming rate of grassland transformation and loss especially through IAPs urgently requires a thorough investigation on methods that could be used in their sustainable management and monitoring. This will offer essential understanding of the impact of IAPs on grasslands.

Numerous programmes have been implemented globally and locally in an attempt to reduce the spread of IAPs (Egoh et al. 2011). These control methods include mechanical, biological and chemical clearing. Mechanical control involves the removal of the IAPs by either cutting and/or burning of the target plant. Biological control makes use of other biological organisms, which are 'natural enemies' to those species, while chemical control involves the use of herbicides, such as picloram (Ahmadi et al. 1980). Indirect control, on the other hand, involves a combination of methods, such as grazing and over-sowing the target area with beneficial plant species (Andreu and Vilà 2011). However, there is a critical need to understand the effectiveness of these control methods. This can be achieved through efficient vegetation monitoring and assessment techniques, which have the ability to periodically access and detect vegetation response after controlling IAPs (Kremen 2005).

In South Africa, conflict of interest species such as Pine, Wattle and Eucalyptus are of particular concern in grassland transformation and loss. These species have derivable value added

products, which are of financial benefit (De Wit et al. 2001, Shackleton et al. 2007). However, they are a threat to the provision of ecosystem goods and services. Even more so in grasslands, where they outcompete the native grass species and alter ecosystem functioning, thus further deteriorating the already compromised and vulnerable biome. Specifically, Wattle species (comprised of *Acacia mearnsii*, *A. baileyana* and *A. dealbata*) are conflict of interest species that were initially introduced in the Eastern Cape province and other areas in South Africa as a commercial plant from Australia so as to derive value added products (De Wit et al. 2001). This is particularly true for rural communities that rely on the resources derived in the form of wood, charcoal and shade (De Wit et al. 2001, Shackleton et al. 2007). Wattle has since spread beyond commercial plantations, invading surrounding vegetation communities, resulting in detrimental effects on biodiversity and water resources (De Wit et al. 2001, Van Wilgen et al. 2001). Several costs and benefit studies have found that the economic cost of invasion by IAPs (including wattle) far outweigh the benefits of its propagation (Van Wilgen et al. 2001, Wise et al. 2012, Vundla et al. 2016). However, none of these studies has been able to give a detailed account on species biodiversity response after clearing IAPs. Additionally, these studies severely relied on the benefits transfer method, which is based on data drawn from other locations and applied in their areas of interest.

Direct ecological methods used to assess the impacts of biological invasions have long been instrumental to conservationist and rangeland managers (Parker et al. 1999, Kumschick et al. 2015). These include technical field survey. For instance Badano and Pugnaire (2004) estimated the impact of *Agave* ornamental invasive plant species on the diversity of native plant species in Spain based on field surveys. They found that the assemblages of native species growing within *Agave* stands had lower diversity than non-invaded sites, however restored sites had the highest biodiversity. Furthermore, several studies have made use of species diversity indices



such as Shannon Wiener's and Simpson's diversity indices in assessing the impacts of IAPS on native plant species diversity (Parker et al. 1999, Badano and Pugnaire 2004, McGeoch et al. 2010, Pyšek et al. 2011).

In this context, grass species diversity and biomass were previously quantified using traditional methods such as field surveys. However, field surveys are spatially limited to local scales and require a lot of time as well as expertise (Lillesand et al. 2014). Consequently, earth observation data is increasingly being applied for vegetation assessments such as grass AGB and species diversity (Pettorelli et al. 2005). Specifically, hyperspectral information has emerged as the most accurate and reliable remotely sensed data, due to its narrow spectral channels that have the ability to detect subtle vegetation changes induced by the variations in the environment. This in turn leads to the alteration of spectral signatures of native vegetation communities (Mutanga and Skidmore 2004). Although the accuracy of hyperspectral data is commendable in vegetation mapping, it is often associated with high acquisition costs while they have high collinearity issues thus making it a challenge to acquire and process. This has led the earth observation community to rely on broad band sensors that are cheap and readily available. Few studies have investigated the application of broad band sensors in monitoring native vegetation restoration success. For instance, Honnay et al. (2003) in an exploratory study found that plant species diversity can be monitored and predicted using Landsat Imagery using the strength of the coefficient of determinant variable. A separate study on invasive alien grass species found out that the thinning of alien plants and changing fire regimes significantly increases grassland productivity through measuring grass AGB (Brooks 2000). However, Brooks et al. (2004) did not spatially represent the findings and no accuracy assessment was conducted. These studies have been successful in outlining the impacts of IAPs. Additionally, these studies were more

concerned with the strength of the relationship between remotely sensed data and measured variables. However, there is still need to identify efficient and accurate methods that can be used to assess the quality and quantity of grasslands after restoration initiatives using remotely sensed data.

Broadband sensors such as Landsat and SPOT have proven to be invaluable in estimating and modelling vegetation traits, such as biomass and species diversity (Ghebremicael et al. 2004, Asner et al. 2008, Darvishzadeh et al. 2008, Mutanga et al. 2012, Grant et al. 2013). However, limitations of broadband multispectral sensors, such as Landsat, is that their broad wavebands do not cover the critical regions such as the red edge, which are instrumental and therefore required in mapping vegetation characteristics such as those induced by different levels of wattle infestations (Thenkabail et al. 2002, Adam et al. 2010). The response of vegetation particularly in the red edge and near infrared wavebands has made these regions of the electromagnetic spectrum to be important in vegetation mapping studies as shown by Mutanga and Skidmore (2004), Cho et al. (2007), Cho and Skidmore (2009) and Sibanda et al. (2015). Of particular interest, is that the red edge spectrum is associated with plant accurate estimations of changes in the structural and biochemical traits such as biomass, leaf angle distribution (LAD) chlorophyll and foliar nitrogen that directly influence the reflectance of vegetation (Broge and Leblanc 2001, Ustin et al. 2004, Cho and Skidmore 2006, Cho et al. 2007, Clevers and Gitelson 2013). This has shifted the focus in vegetation mapping studies to sensors such as Sentinel 2 multi spectral imager (MSI) that cover this region of the electromagnetic spectrum.

Specifically, Sentinel 2 MSI as a free new generation sensor covering the critical red edge spectrum of the electromagnetic spectrum is invaluable in assessing the impact of invasive alien plant species. Sentinel 2 MSI has a spatial resolution ranging from of 10-60m. and a spectral

resolution of 13 spectral wavebands with three bands in the red edge region of the electromagnetic spectrum. The higher spatial and spectral resolution of Sentinel 2 MSI make it invaluable to vegetation restoration success monitoring. Additionally, as a freely available broadband sensor, Sentinel 2 MSI is the practical option.

Literature further illustrates that the integration of data from new generation of sensors such as Sentinel 2 MSI and Worldview that cover the red edge region with robust machine learning algorithms improves the prediction accuracy of vegetation traits such as biomass and species diversity in invaded, and restored grassland sites (Mountrakis et al. 2011, Verrelst et al. 2012). For instance, partial least squares regression (PLSR) is a bilinear method that reduces collinearity of spectral variables. PLSR has been shown to not only reduce the number of spectral variables for analysis but, also increases accuracy of the developed prediction model by up to 23 % (Hansen and Schjoerring 2003). The integration of PLSR with remotely sensed data has proven to be useful in characterising vegetation traits based on remotely sensed data (Hansen and Schjoerring 2003, Sibanda et al. 2018). For instance Sibanda et al. (2018) illustrated that the combination of Sentinel and PLSR was instrumental in characterising canopy storage capacity for hydrological applications in wattle infested ecosystems using Sentinel-2 MSI derived red edge bands. The above-mentioned advantages of PLSR derived models make it a useful tool in predicting grassland vegetation. Therefore, this study sought to use partial least squares regression (PLSR) and sentinel 2 MSI remotely sensed data in mapping grass above ground biomass and species diversity in areas under different levels of wattle invasion.

### **1.1.1. Research objectives**

The aim of this study was to evaluate the use of remotely sensed (sentinel 2 MSI) data in determining the impacts of wattle on above ground biomass and diversity of native grass species.

The overarching hypothesis was that wattle invasion and density negatively affects species diversity and productivity of native grass species. The specific objectives were as follows:

- To investigate the utility of Sentinel 2 MSI remotely sensed data as a cost-effective and quick assessment technique for mapping AGB of native grasses under different levels of *Acacia baileyana*, *A. dealbata* & *A. mearnsii*, invasion.
- To investigate the applicability of Sentinel-2 MSI derived data to detecting grass species diversity across different levels of wattle invasion in an alpine grassland.

### **1.1.2. Research questions**

Can Sentinel 2 MSI derived spectral variables offer reliable and accurate estimates of grass AGB and grass species diversity in a wattle invaded and wattle cleared grassland system?

Does the extent of wattle invasion alter grassland vegetation structure through changing biodiversity and dominance in grasslands and whether wattle invasion density and cover, alter grass AGB?

### **1.1.3. Thesis outline**

This dissertation is comprised four chapters. An introductory chapter, two results chapters and a synthesis chapter. The second chapter investigates the applicability of remote sensing data as a cost-effective and quick assessment technique of the ecological response of native grasses to invasion by *Acacia baileyana*, *A. dealbata* & *A. mearnsii*. The third chapter investigates the

application of Sentinel 2 MSI in assessing the biodiversity impacts of wattle invasion on native grass species

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## 2. QUANTIFYING GRASS PRODUCTIVITY USING REMOTELY SENSED DATA: AN ASSESSMENT OF GRASSLAND RESTORATION BENEFITS.

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### 2.1 .Abstract

This study sought to evaluate the utility of remotely sensed data in estimating the impact of wattle invasion and clearance on native grass species productivity using Sentinel 2 multispectral instrument (MSI) and partial least squares regression (PLSR). To accomplish this, the study

assessed aboveground biomass (AGB) at various levels of wattle invasion. The levels of wattle invasion investigated were cleared, uninvaded, moderately invaded and heavily invaded. In assessing the impacts of wattle invasion on grass AGB the study found that, wattle invasion significantly reduces grass AGB when compared to uninvaded and cleared plots. Specifically mean grass AGB was 89.636g/m<sup>2</sup>, 43.869g/m<sup>2</sup> and 83.363g/m<sup>2</sup> for the cleared, moderately invaded and uninvaded, respectively. The study further found no significant differences between cleared and uninvaded plots. However, significant differences were observed across the other plots. In assessing the applicability of remotely sensed data, the findings of this study showed that vegetation indices optimally estimate biomass compared to standard wavebands. The most influential variables in estimating biomass were red-edge based vegetation indices (VIs). Specifically, the simple ratio VI (band5/band2) was the most optimal variable for predicting grass AGB across various levels of wattle invasion yielding high accuracies (RMSEP=191.1g/10m<sup>2</sup> and R<sup>2</sup>=0.8268). This study also showed that following restoration, grass biomass in cleared areas is not significantly different from areas with no wattle invasion, indicating that restoration in the area was successful. Overall, the results underscore the utility of remotely sensed data in monitoring grassland degradation and restoration.

**Keywords:** Acacia, wattle, biological invasion, productivity loss, above ground

biomass, Sentinel-2 MSI

## **2.2 .Introduction**

Invasive alien plant species (IAPs) have long been a threat to various ecosystem types globally. Specifically, invasion of grasslands by woody IAPs results in water loss through higher evapotranspiration rates in invasive plants as compared to native plants (Le Maitre et al. 2000, Cavaleri and Sack 2010). Also, woody IAPs, alter the carbon balance through the transfer of soil carbon into invading plants, leading to the displacement of native vegetation and this can directly

translate into lowered productivity particularly in grassland systems (Gordon 1998, Jackson et al. 2002, Didham et al. 2007, Hejda et al. 2009). Ultimately, this causes malfunctioning of the ecosystem and its associated services, thus further degrading the environment. In grassland systems, ecological restoration is increasingly becoming the preferred approach for promoting the re-introduction of native grass and forbs species, thus restoring the functioning of the grassland ecosystem and services it provides (Martin et al. 2005, Joyce 2014, Baasch et al. 2016). Grassland restoration includes the removal of invading species (physical, mechanical and chemical clearing) and active reintroduction of native species. However, these restoration initiatives can be costly. For instance in the United States of America, Pimentel et al. (2005) estimated that more than US\$3 billion per annum is spent on herbicides alone for the controlling of IAPs. In South Africa more than 3.2 billion rands (US\$457 million or US\$30 million per annum) had been invested into the control of alien invasive plants by the year 2012 since 1994 (van Wilgen et al. (2012). Such large expenditure needs to be sufficiently supported by extensive quantitative research to inform costbenefit analyses, particularly in the public sector as the principal funder of clearing initiatives. However, quantification of the costs and benefits of restoration (to motivate the large expenditure) is hampered by the unavailability of rapid regional quantitative data (particularly the ecological response to disturbance) (Wainger et al. 2010). In this regard, there is a need for more studies to backup investment into the clearing of invasive alien plants and inform cost benefit analysis. The monitoring of various biophysical and ecological parameters of grasslands, provides essential information on their health, productivity and response to disturbances such as grazing and fire. Furthermore, this information can provide crucial information in the estimation of restoration success or the lack thereof (Malmstrom et al. 2009). In addition, information is essential for land managers, especially with the increasing need for quantitative estimates of socio-economic benefits from restoration initiatives (Malmstrom et al. 2009). Studies by Van Wilgen et al. (1996)



and Crookes (2012) made use of ecological data to conduct cost-benefit analyses of restoration initiatives for policy. Such studies highlight the lack of sufficient site specific data required to complete cost benefit studies. The ecological and economic importance of grasslands is recognised nationally and globally. This warrants the need to quantify the gains and losses in grassland productivity due to invasion and restoration in a cost effective manner.

Grass above ground biomass (AGB) has been identified as an important parameter for grass productivity in grassland and rangeland assessments (Breckenridge et al. 1995, Joyce 2014, Baasch et al. 2016). Specifically, grass AGB is an important indicator applied for regional and global modelling of ecosystem processes, both biophysical and ecological (Song 2013). In vast grasslands, biomass can provide key insights into forage production for livestock grazing as well as monitoring grassland recovery following restoration initiatives (Purevdorj et al. 1998). In this regard, there is a need for regular and accurate measurement of grass AGB in these grassland areas. Ground based methods are widely used to measure biomass in southern Africa due to their higher accuracy in estimating grass AGB. However, ground-based (traditional) methods can be destructive, laborious and are limited to local scales (Tucker. 1980). Thus, there is a growing need of regional scale assessment of biomass that overcome the limitation of ground-based methods of estimation.

To combat this, earth observation (EO) data from space borne sensors, offers broad scale reliable and cost-effective detection and estimation of biomass. Specifically, Mutanga et al. (2012), Sibanda et al. (2017) and Ramoelo et al. (2015) were successfully able to predict grass AGB using remotely sensed data. Mutanga et al. (2012), using WorldView-2 imagery, was able to predict grass biomass at high accuracies with root mean square error of prediction (RMSEP) of 0.441 kg/m<sup>2</sup> based on the random forest algorithm and Worldview red-edge and NIR bands. Also using

WorldView-2 imagery, Sibanda et al. (2017) when comparing grass biomass under different fertilizer treatments, noted that the combination of texture models and red-edge wavebands improved AGB prediction with a RMSEP 0.2 kg/m<sup>2</sup> across all grassland fertilizer treatments. Although there are several studies, which have used remotely sensed data to estimate AGB, very few of them have been conducted to assess grassland restoration using remotely sensed data. Malmstrom et al. (2009) used Landsat imagery to assess restoration successes in previously weed infested forage areas. The study investigated four management options for private landowners, specifically simple burn, native grass seeding, pasture mix seeding and native grass seeding mixed with additional intervention over a period of five years. The study found that there were significant gains in biomass amounting to 100kg/ha following restoration. Although the above-mentioned studies showed a strong correlation of grass AGB with various remotely sensed variables and derived vegetation indices, they utilised data that is either expensive and limited to local scales such as Worldview or they used sensors that do not cover the strategic sections of the electromagnetic spectrum crucial for vegetation mapping such as Landsat. However, the new generation sensors such as Sentinel-2 MSI imagery, with three red-edge bands and NIR band as well as optimal spatial resolutions (i.e. 10, 20m) could offer more reliable and accurate estimates of grass AGB compared to Landsat 8 OLI (Mutanga and Skidmore 2004, Mutanga et al. 2012, Sibanda et al. 2015). Specifically, Sentinel 2 MSI boasts a wide swath width of 290 km, high spectral (13 bands) and spatial resolution of up to 10m. These wavebands, further improve the accuracy of mapping biomass when combined with robust algorithms such as PLSR.

Furthermore literature shows that VIs derived from bands that cover the red-edge and near-infrared (NIR) regions of the electromagnetic spectrum are important for the estimation of grass AGB (Mutanga and Skidmore 2004, Sibanda et al. 2017). The red-edge portion of the electromagnetic

spectrum improves the accuracy in the estimation of grass variables including grass AGB, because of its sensitivity to slight changes in the reflectance of vegetation due to plant characteristics and physiology (Cho et al. (2007), Mutanga and Skidmore 2007, Cho and Skidmore (2009), Mutanga et al. 2012, Schumacher et al. 2016).

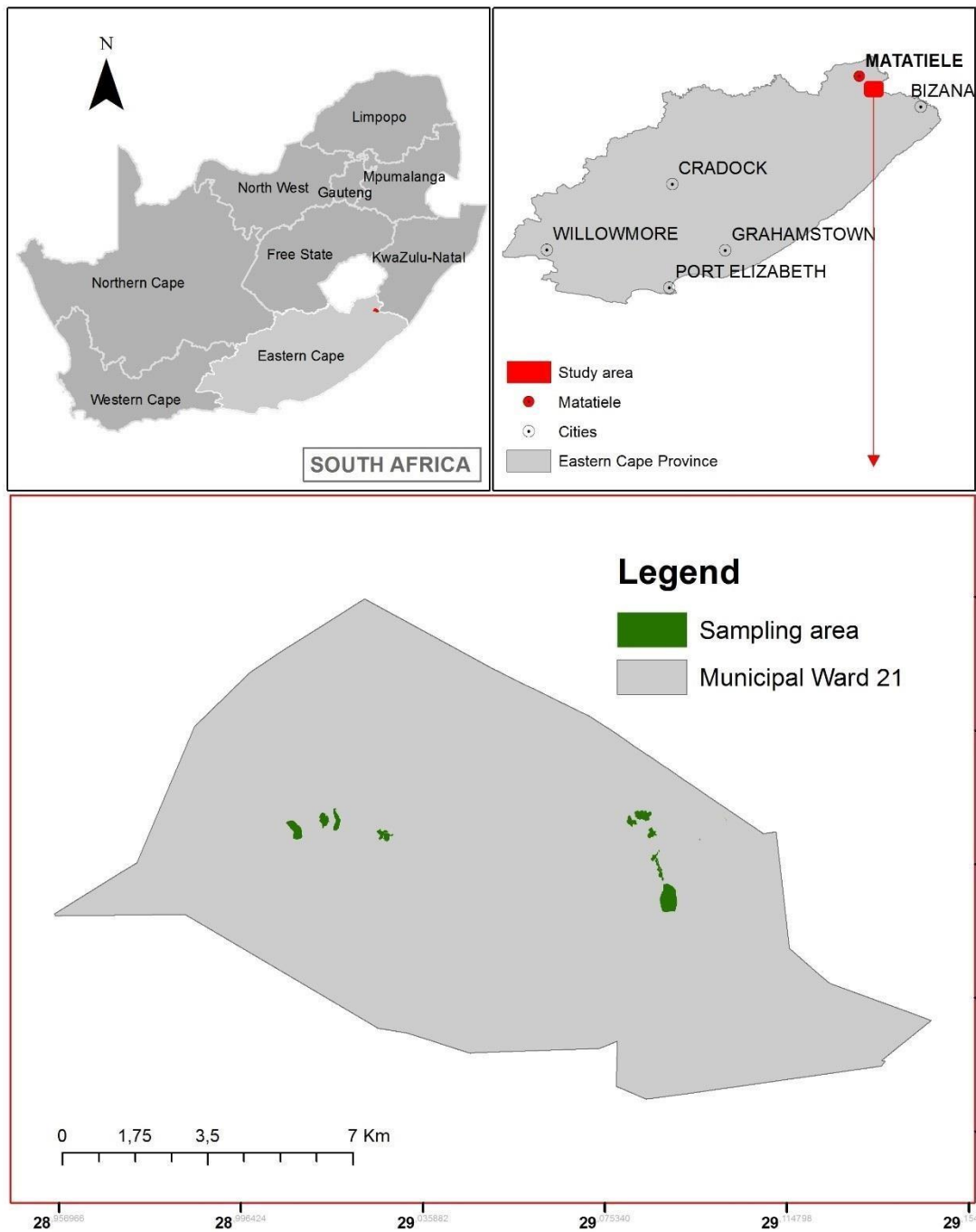
Vegetation indices are renowned for their heightened sensitivity to detecting AGB (Asrar et al. 1984). The plight of broadband vegetation indices is that critical information can be lost thus affecting the accuracy of remote sensing findings (Hansen and Schjoerring 2003). Thus, there is a constant need to improve the performance of vegetation indices, using new information provided by recent sensors. The Sentinel-2 MSI image data with three red edge bands promises a cost effective technique for the detection of grass AGB.

The integration of optimal remotely sensed data and derived vegetation indices with robust machine algorithms such as PLSR increases the AGB estimation accuracies. For instance Cho et al. (2007) illustrated that the incorporation of PLSR improved the estimation accuracies from 331g/m<sup>2</sup> to 149 g/m<sup>2</sup> . In that regard, we hypothesized that the freely available Sentinel 2 MSI remotely sensed data combined with derived VIs could provide sufficient information required to evaluate the success of grassland restoration from wattle removal using the PLSR model. This study therefore, sought to investigate the utility of Sentinel 2 MSI remotely sensed data as a costeffective and quick assessment technique of the ecological response of native grasses to invasion by *Acacia baileyana*, *A. dealbata* & *A. mearnsii*, herein referred to as wattle species. Specifically, PLSR models derived from Sentinel 2 MSI spectral bands and derived VIs (NDVI and SR) were used in estimating grass AGB as an indicator of grassland productivity following restoration activities.

## **2.3 .Materials and Methods**

### **2.3.1 Site description**

The study was conducted in two rural villages within the Matatiele local municipality in the Eastern Cape Province of South Africa (Figure 1). These villages were Mabheleni (-30.563 611S, 29.089 626E) and Msukeni (-30.552597S, 29.018790E). These sites were selected because they were located in predominately wattle-invaded grasslands that have had intensive investment into the clearing of wattle. The studied areas fall within communal lands that are intensively grazed by cattle.



Mabheleni

Msukeni

Figure 2.1. Study area in relation to the Eastern Cape Province and South Africa (a) and the detailed study area overlain by municipal boundary (b)

### **2.3.2 Field data collection and processing**

Field data collection was conducted during the peak productivity stage of grasses in April 2017. A stratified random sampling approach was adopted for this study. Prior to the field survey, the study area was split into four different strata, namely wattle heavily invaded, moderately invaded, uninvaded and cleared sites using the Google earth platform and maps provided by Conservation South Africa for verification. Heavily invaded sites were those characterised by a full coverage of the ground by wattle canopies, while moderately invaded sites were wattle infested but not fully covered by wattle canopies. Uninvaded sites had no history of wattle invasion while cleared sites had been cleared by Conservation South Africa of wattle in the past 5 years. However, on-site, the heavily invaded treatment had little to no grass hence it was excluded from the analysis. Random points were generated within each of the stratum using the hawths analysis tool in ArcGIS®, with a condition to generate high density and representative samples. Within each stratum, 120 samples were generated, yielding a total of 480 sample points. The random points were located using a handheld Garmin etrex 10 (GPS) with an estimated accuracy of  $\pm 5$  m during the field survey. These points were then used as centres of the 0.5m by 0.5m sampling quadrats. Within each quadrat the wet above ground biomass of grasses was measured and recorded. To get wet grass biomass in each quadrat, dry material was removed from the cut plant and the wet biomass was measured using a digital scale in the field. The data was stored in table format and appended to the point map in a GIS environment. To account for Sentinel-2 MSI's spatial resolution, the sampling points were then overlaid with a 10m by 10m grid. Biomass samples from the sub plots that fell within the same 10m by 10m grid were averaged and the grid centre co-ordinates were then used for extracting the spectral signatures for the analysis. On average, 3 samples fell within the 10m by 10m grid. The final sample size used for analysis was 182. Following the resampling procedure, the mean biomass within each 10m grid was then expressed as  $\text{g/m}^2$ . The 10m plots were then

tested for spatial autocorrelation based on the Moran's I index, and were proven not to be affected by autocorrelation.

### **2.3.3 Remotely sensed data extraction and pre-processing**

A Sentinel-2 MSI image covering the study area was acquired for the period that coincided with field data collection. Specifically, a cloud free image was selected and downloaded from United States Geological Survey (USGS) Earth Resources Observation Science centre archive (<http://earthexplorer.usgs.gov/>). Sentinel-2 MSI image data consists of 13 spectral bands with a spatial resolution ranging from 10m to 60m.. The acquired Sentinel-2 MSI image was atmospherically corrected in QGIS using the Semi-Automatic Classification Plugin (SCP). The bands that were considered in this study were those with a spatial resolution of 10 and 20. Bands 1, 9 and 10 are not suitable for vegetation related studies thus they were not considered in this study. The Sentinel-2 MSI wavebands considered in this study (B5, B6, B7, B8a, B11 and B12) were resampled using the constant ground Sampling Distance of 10m derived from the visible bands (B2 B3 B4 and B8). Using the Sentinel-2 MSI satellite images, NDVI and SR vegetation indices were computed from all possible band combinations. The point map created using centre locations of the 10m plots were overlaid with the corrected Sentinel-2 MSI image to derive spectral signatures in ArcGIS 10.3.

### **2.3.4 Statistical analysis**

To quantify the impacts of wattle invasion on grassland productivity, exploratory data analyses were conducted in SPSS. The Kolmogorov-Smirnov normality test was conducted to test whether the data met the requirements for a parametric statistical assessment. Upon normality confirmation of the data,

a one-way Analysis of Variance (ANOVA) was used to test whether there were significant differences in biomass across cleared, uninvaded, moderately invaded and heavily invaded treatments at ( $\alpha = 0.05$ ) significance level. This was followed by a post-hoc Tukey test to determine where differences between the treatments were. Partial least square regression (PLSR) analysis was then used in this study to predict grass AGB. PLSR is an algorithm with the ability to examine variables with high collinearity (Fan et al. 2011). Estimation of biomass using remotely sensed data was only conducted for the three treatments i.e. cleared, uninvaded and moderately invaded. The heavily invaded site was excluded as the canopy cover restricted grass reflectance, additionally, most of the sampled quadrats had little to no grass in them.

The leave one out cross validation (LOOCV) procedure was conducted in estimating grass biomass using remotely sensed data. Full explanation on the LOOCV method can be found in Chauchard et al. (2004). The accuracy and performance of the PLSR model derived from LOOCV were evaluated using the root mean square error of prediction (RMSEP) and the coefficient of determination ( $R^2$ ). The full sequence of the statistical analysis conducted in this study is illustrated in Table 1. Variable importance (VIP) scores for each treatment were then generated and used to determine which variables optimally contributed to the best PLSR models for estimating grass biomass. The variables with VIP scores above one were selected and used in the following stage of the analysis while those that were less than one were discarded. This was conducted for all treatments. The PLSR algorithm was repeated using the variable with VIP scores above one for at least two of the three treatments. The models with the lowest RMSEP and highest  $R^2$  were used for the final prediction of biomass.

Table 2.1. Sentinel-2 MSI spectral bands and vegetation indices used at the different stages of the analysis.



Stage Analysis	Variable	List of variables
I	Raw Bands	Visible (band 1, 2, 3, 4), Red-edge (band 5,6,7,8,8a) Shortwave infrared (band 9 and 12)
II	Vegetation indices	Normalised Difference Vegetation Index: NDVIs Simple Ratio: SRs
III	Spectral Bands and Vegetation indices	Combination of best performing spectral bands and vegetation indices

## 2.4 Results

### 2.4.1. Statistical analysis

In this study, prior to any confirmatory statistical analysis, exploratory data analysis was conducted as detailed in the following section.

### 2.4.2. Exploratory analysis

Descriptive statistical analysis showed that data did not significantly ( $\alpha > 0.05$ ) deviate from the normal distribution curve hence it met the basic assumptions for parametric statistical analysis.

An ANOVA test was subsequently conducted to compare means across treatments. Based on the ANOVA, significant differences across the three treatments with  $\alpha < 0.05$  were observed ( $F = 10.33$ ;  $F_{crit} = 3.06$ ) (Figure 2.2).

The Tukey post hoc analysis established no statistical significant differences between cleared and uninvaded plots only (Figure 2.2 & Table 2.2). However, the grass biomass in the heavily and moderately invaded plots were significantly lower than the cleared and uninvaded plots.

Table 2.2 shows results of the post hoc analysis.

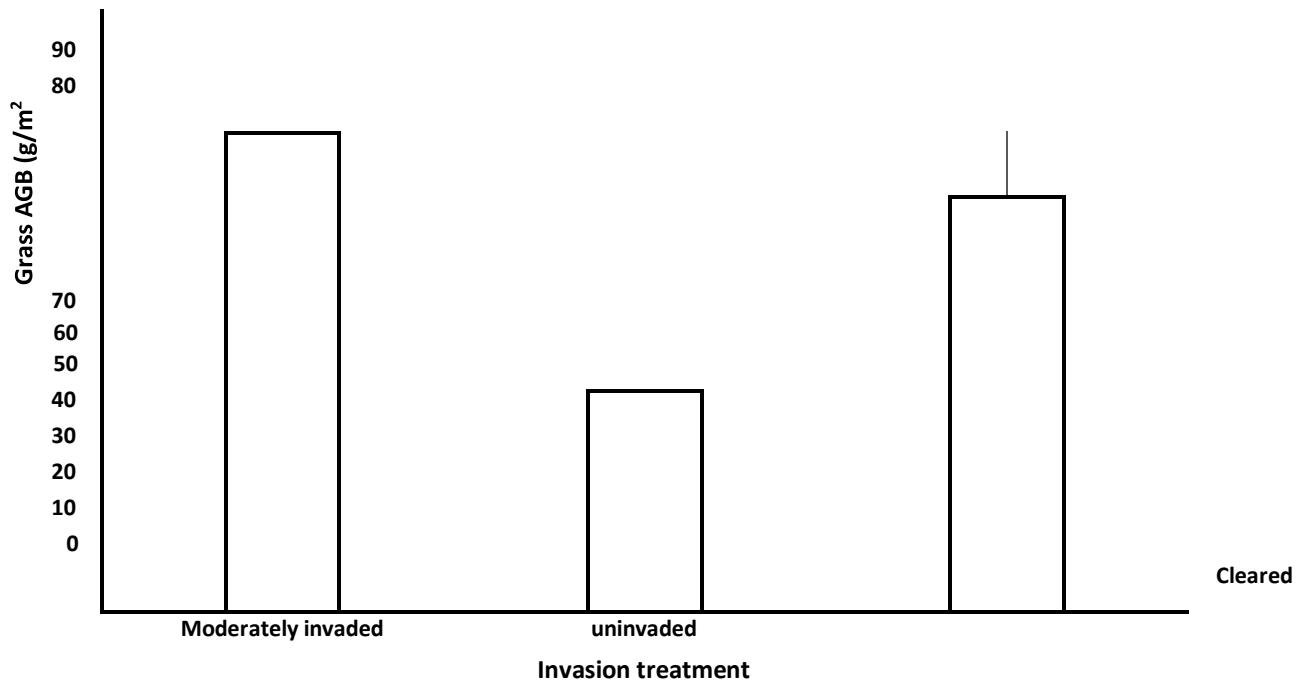


Figure 2.2. Mean AGB grass biomass, with standard error bars at 95% confidence intervals across various levels of wattle invasion.

Mean grass biomass was 89.636g/10m<sup>2</sup>, 43.869g/10m<sup>2</sup> and 83.363g/10m<sup>2</sup> for the cleared, moderately invaded, and uninvaded respectively. Wattle invasion reduces grass AGB (Figure 2.2 & Table 2.2).

Table 2.2. Level of significance ( $\alpha = 0.05$ ) of grass AGB between treatments with insignificant differences in bold

	Moderately invaded	Cleared
Moderately invaded		>0.0001
Cleared	>0.0001	
Uninvaded	0.001	<b>0,826</b>

### 2.4.3. Estimation of grass AGB biomass using wavebands and vegetation indices

The raw spectral bands derived PLSR model had a RMSEP of 22.92g/m<sup>2</sup>, 21.02g/m<sup>2</sup>, and 27.9g/m<sup>2</sup> for the moderately invaded, uninvaded and cleared plots, respectively (Figure 2a-c).

While for the SR derived PLSR model, the RMSEP was 19.38 g/m<sup>2</sup>, 18.63 g/m<sup>2</sup> and 19.18 g/m<sup>2</sup> for the moderately invaded, uninvaded and cleared plots, respectively (Figure 3d-f). For the NDVI derived PLSR model, the RMSEP was 13.06g/m<sup>2</sup>, 14.93g/m<sup>2</sup> and 15.03g/m<sup>2</sup> for the moderately invaded, uninvaded and cleared plots, respectively (Figure 3g-i). The performance of the developed model varied across treatments, with the moderately invaded treatment based on NDVI yielding the lowest RMSEP (13.06g/m<sup>2</sup>) as shown in figure 3g. Specifically, the developed model was able to predict AGB across all treatments at reasonably low RMSEP.

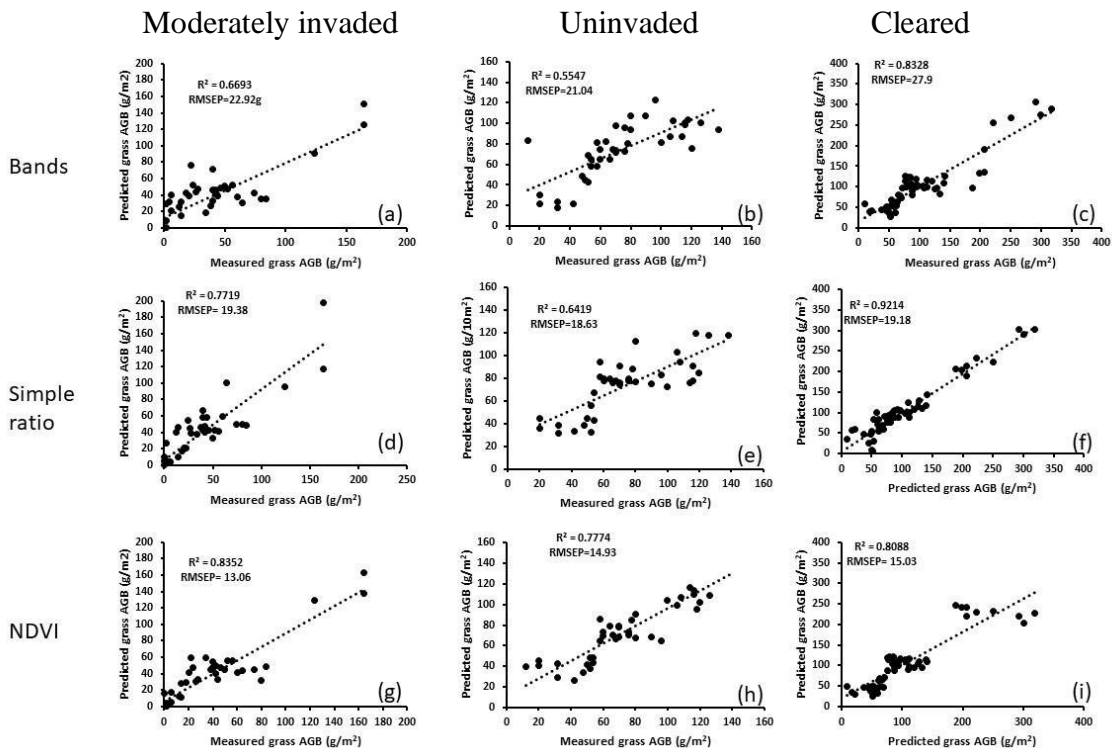


Figure 2.3. Grass AGB estimation performance for the different treatment and Sentinel-2 MSI variables showing both the correlation coefficient and the RMSEP. Grass estimates at different levels of wattle invasion, namely, moderately invaded (a, d, g) uninvaded (b, e, h) and cleared (c, f, i) predicted from raw band (a-c), simple ratio (d-f) and NDVI (g-i).

The highest coefficient of determination  $R^2$  was for the cleared simple ratio derived PLSR model (Figure 2.3i) while the lowest was the spectral bands derived PLSR model for the uninvaded treatment with a coefficient of determination of 0.55 (Figure 2.3b). The predicted versus measured coefficient of determination from the SR variables is 0.77, 0.64, and 0.92 for the moderately invaded, uninvaded and cleared plots, respectively. For the NDVI variables, the coefficients of determination were 0.83, 0.78, and 0.81 for the moderately invaded, uninvaded and cleared plots, respectively. The coefficients of determination for the raw bands are 0.67, 0.55 and 0.83 for the moderately invaded, cleared and uninvaded sites respectively.

Figure 2.4 shows the waveband frequencies of Sentinel-2 MSI spectral bands, derived NDVI and SR vegetation indices in optimally estimating grass AGB across the three treatments. Sentinel 2 MSI spectral variables that have frequency scores above 1 were regarded as the most optimal variables for estimating grass AGB. It can be observed that the red-edge bands (B5, B6 & B7) had the highest frequencies scores across the three treatments. From the NDVI based models, the band combination with high frequencies, were B5.B3, B6.B2, B6.B3, B7.B2, B7.B3, B7.B4, B8.B2, B4.B7. Meanwhile, from the SR derived models B2.B5, B2.B6, B2.B7, B2.B8, B5.B4, B6.B8a, B7.B12, B8a.B4, B8.B5, B8a.B3 and B8a.B5. band combinations were the most frequent variables in predicting grass AGB across the treatments. These bands are indicated as the bands with a frequency above the dotted line in Figure 4 showing the VIP score across the treatments.

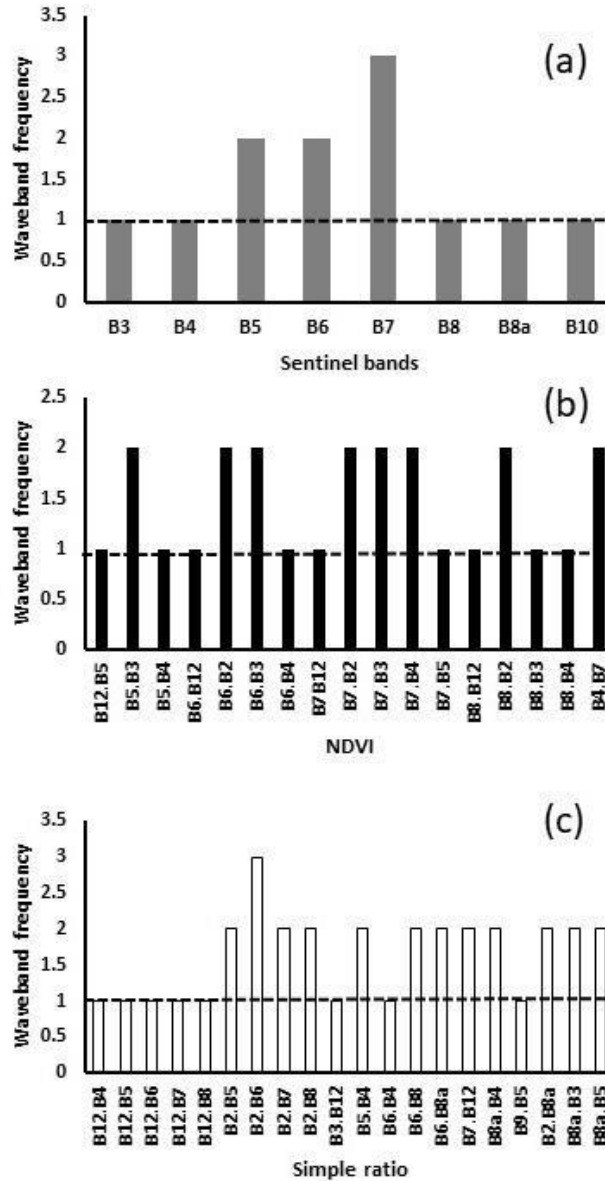


Figure 2.4. VIP scores for the Sentinel-2 MSI derived data variables obtained from estimating biomass using (a) raw spectral bands (b) Normalized vegetation index (c) and the simple ratio vegetation index (c).

#### 2.4.4. Estimation of grass AGB biomass using selected wavebands combined with selected vegetation indices

Figure 2.5a illustrates the VIP scores for all the variables derived using the PLSR algorithm and combined dataset of Sentinel 2 MSI selected vegetation indices and wavebands. When the

optimal variables derived from the preceding analysis stages were combined to estimate grass biomass across the invasion levels, the estimation accuracy decreased from 13.06g/m<sup>2</sup> (for the moderately invaded strata) in the proceeding stage of analysis to a RMSEP of 27.9 g/m<sup>2</sup> as shown in Figure 2.5b. The most influential variables were SR B5/B2 and SR B8/B5, and B5 in order of importance. In addition, a higher coefficient of determination of  $R^2 = 0.8268$  was obtained from the combined data across all three treatments (figure 2.5b).

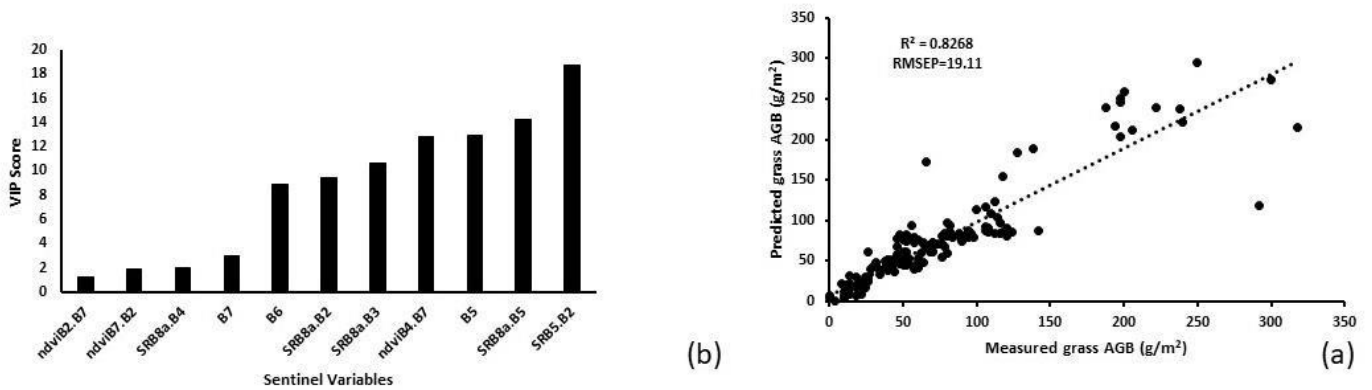


Figure 2.5. VIP scores for the Sentinel-2 MSI derived biomass across all treatments (a) and (b) showing measured versus predicted relationship of grass biomass across different levels of wattle invasion

Figure 2.6 illustrates the spatial distribution of biomass across the three treatments based on the most optimal variables in predicting grass AGB. The derived model predicts the highest biomass at 301.652g/m<sup>2</sup> and the lowest at 1.378g/m<sup>2</sup>. The uninverted plots (figure 6c & f) have predicted biomass in the higher regions i.e. more productive, with the lower ranges of biomass predicted in the moderately invaded and cleared plots. Biomass is much more reduced for the moderately invaded plot.

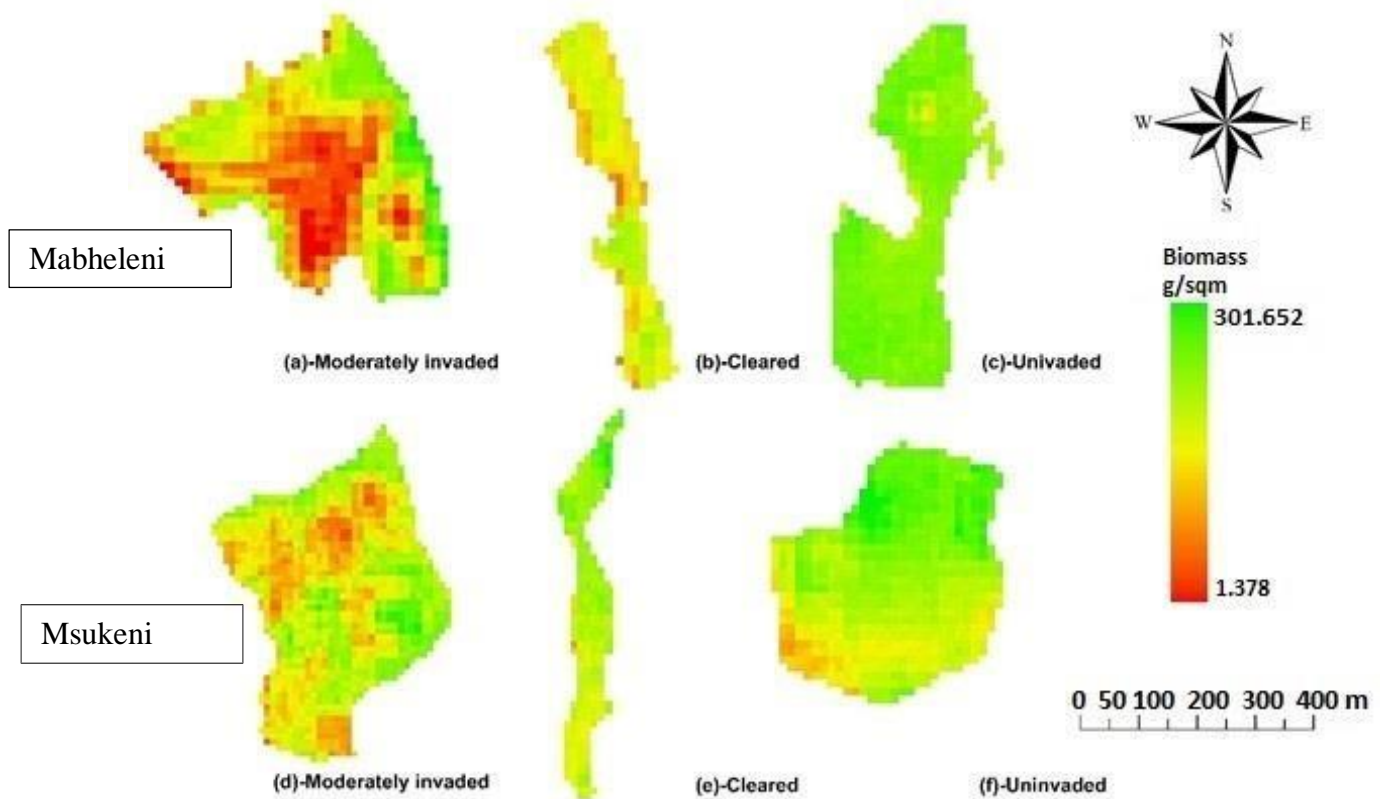


Figure 2.6. Spatial distribution of grass AGB across different levels of wattle invasion, using the most optimal PLSR model in Mabheleni and Msukeni villages. Grass AGB is derived from applying the PLSR model to the Sentinel-2 MSI image data.

## 2.5. Discussion

The growing need for the quantification of the costs of alien invasive species and the benefits relating to their control requires efficient and accurate measures of their impact on natural resources. Thus, this study investigated the applicability of remotely sensed data as a cost-effective and quick assessment technique of the ecological response of native grasses from wattle species invasion and clearing. This study also sought to establish the optimal variables for the estimation of grass AGB across various levels of wattle invasion, thus ultimately applying remote sensing to restoration ecology.

The findings of this study showed that combining the red-edge bands with vegetation indices amplifies the accuracy of the results by up to 50% (from a RMSEP of 27.9 g/10m<sup>2</sup> for raw bands to RMSEP of 13.06g/10m<sup>2</sup> from SR). Vegetation indices enhance the accuracy of information derived from remotely sensed imagery (Baret and Guyot 1991). Combining vegetation indices with red edge bands further enhances the accuracy and reliability of the predicted variables. For instance, Chen et al. (2009) found that vegetation indices combining red-edge and visible bands increased the accuracies of the estimated biomass in grassland areas with low grass AGB. Using Sentinel 2 MSI image data, we found that the simple ratio derived vegetation index (red edge and blue regions) and raw band in the red edge region were the most important variable to grass AGB prediction and detection in grasslands. The chlorophyll in green vegetation absorbs visible energy (particularly in the blue and red wavelengths) for use during photosynthesis. The importance of the red edge and blue band based simple ratio index is attributed to the abrupt changes in vegetation reflectance characteristics in the red edge region, which are primarily driven, by the chlorophyll absorption and leaf internal scattering in the NIR. This makes the red edge particularly unique in vegetation detection studies. Additionally, the blue band which is sensitive to atmospheric effects has been used by Kaufman and Tanre (1992) to overcome the short comings of the traditional NDVI vegetation index by incorporating the blue band to auto correct for atmospheric effects. These factors could be used to explain the changes in reflectance properties of the estimated biomass.

Grass AGB prediction across different levels of wattle invasion at high accuracies can also be attributed to the suppression of grass productivity by the shade of invading wattle species. The varying effects of wattle on grass productivity can be detected through remote sensing through the different reflectance characteristics associated with physiological impacts of plant stress.



Specifically, the health, leaf area and leaf density tends to vary between grasses that are shaded when compared to those that are not shaded (Knipling 1970). This consequently changes the photosynthetic potential of the grasses across the various levels of wattle invasion, ultimately affecting the reflectance of these grasses in the red edge.

### **2.5.1 The impact of wattle on AGB of grasses**

High grass productivity is essential, particularly in rural rangelands where the communities extensively use the land for livestock grazing. Forage production for livestock in rangelands is the main ecosystem service jeopardised by the invasion of wattle. This study found that both moderately and heavily invaded sites had reduced grass AGB and subsequent grazing land. Treegrass interactions are driven by competition and facilitation as described by Scholes and Archer (1997). At low densities, isolated tree species can have a facilitative role on grass biomass. However, the competitive nature of wattle and its invasion intensity has resulted in the reduction of grass productivity. The allelopathic interaction coupled with the competitive advantage for light that wattle exhibits is the main factor resulting in the reduced grass AGB in wattle invaded areas (Fatunbi et al. 2009). The leaves of wattle through allelopathy interactions suppress herbaceous grass growth. Additionally, by shading out understorey grass species and placing the grass species under stress, native grass species become easily outcompeted by wattle. This is, however, in contrary to the findings of Belsky (1994), who showed that understorey productivity was enhanced by the shading. The differences noted in the findings by Belsky (1994) and those of this study could be explained by the fact that their study was based on indigenous trees species that have less negative allelopathic consequences, whereas this study focused on grass. This suggests that the impacts of native woody species invasion may not be as deleterious as that of invasive alien woody species.

Additionally, in assessing whether clearing restores grass AGB, this study investigated changes in grass AGB in restored grasslands compared to invaded plots. Initial clearing of wattle was conducted in 2013, making it possible to show the gains in grass biomass following the clearance. Results of this study showed that grass AGB in the cleared treatment was higher than the moderately invaded treatment. This indicates that there are productivity benefits of clearing wattle species on indigenous grass species. The results of this study concur with several studies investigating the changes in grass productivity. For instance, Laxson et al. (1997) estimated gains of up to 45 % following the removal *Prosopis*. This study was conducted on a communal land tenure, where livestock production is an important source of livelihoods. In that regard, grazing is one of the most critical factors which affects several aspects of grasslands including productivity in this area (Watkinson and Ormerod 2001). The potential benefits from restoring invaded sites could be limited by the poorly managed grazing in the communal areas. Communal grazing areas are largely impacted by overgrazing, which is ultimately a result of the tragedy of the commons.

## **2.6. Conclusions and recommendations.**

Results of this study suggest that Sentinel-2 MSI 2 derived vegetation indices can optimally characterise grass AGB at various levels of wattle invasion. The monitoring of the impacts of wattle invasion on invaded and restored sites is vital for conservation biology and rangeland management. Understanding how invasive species invasion and clearing affects rangeland productivity will inform stocking rate, the grazing management systems implemented and conservation plans of the area. The findings of this study are crucial in informing natural resource management through providing effective methods for the quantification of restoration success or failures ecologically. Future research in the area should investigate the more important drivers in

grassland degradation in the area, between grazing and invasion by wattle species. Additionally, future research should investigate the biodiversity impacts of clearing to get both the economic and ecological impacts of wattle invasion on native grasses.

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### **3. REMOTE SENSING THE IMPACTS OF WATTLE INFESTATION ON GRASS BIODIVERSITY IN AN INTENSIVELY UTILISED COMMUNAL GRASSLAND SYSTEM.**

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#### **3.1. Abstract**

Biodiversity monitoring is increasingly becoming crucial for achieving conservation goals and targets. In that regard, this study sought to investigate the utility of remotely sensed data in assessing the impacts of wattle invasion and clearing on native grass species diversity. Specifically, this study evaluated the potential of Sentinel-2 multispectral instrument (MSI)

spectral data and partial least squares regression (PLSR) to predict grass species diversity across uninvaded,

1 moderately invaded, and heavily invaded alpine grasslands. To achieve this objective, the study  
2 compared the performance of spectral bands; derived ratio (SR) and normalised difference  
3 vegetation (NDVI) indices computed using all possible band combinations in predicting grass  
4 species diversity. Furthermore, the study sought to assess which ecological diversity index was  
5 better-characterised using remotely sensed data across different levels of wattle invasion. Results  
6 of this study showed that Sentinel-2 MS derived data optimally predicted Shannon Wiener's  
7 diversity index to an rRMSE of 22.06, 24.37, and 22.189 for the cleared, moderately invaded and  
8 uninvaded treatments, respectively and sub-optimally predicted the Simpson diversity to a rRMSE  
9 of 23.64, 27.25, and 18.96 for the cleared, moderately invaded and uninvaded treatments,  
10 respectively. While species richness was predicted with rRMSE of 22.17, 28.14 and 19.10 for  
11 cleared, moderately invaded and uninvaded treatments. Subsequently, the Shannon Wiener's index  
12 was then used to predict grass species diversity across wattle cleared, uninvaded and moderately  
13 invaded alpine grasslands to a RMSE of 0.2145 and  $R^2$  of 0.6392. The most influential spectral  
14 variables were, bands 5 and 6, NDVI, computed from bands 6 and Band 3. The findings of this  
15 study show that Sentinel-2 MSI spectral variables offer reliable and accurate estimates of grass  
16 species diversity.

17 **Keywords:** Acacia, wattle, biological invasion, Simpson diversity, Shannon Wiener, Sentinel2  
18 MS

## 19 20 **3.2. Introduction**

21 Biological invasion is globally the second biggest threat to biodiversity after habitat loss (Sala et  
22 al. 2000). At a global scale, invasive alien species are major drivers of ecological change (Vilà et  
23 al. 2011). For instance, in a meta-analysis, Vilà et al. (2011) found that the impacts of invasive

24 alien plant species (IAPs) on native plant species community structure were more substantial  
25 compared to ecosystem functioning. Essentially highlighting the direct impacts of IAPs on native  
26 plant diversity. The spread of IAPs is of paramount concern to plant species diversity, thus  
27 advocating the need for effective control measures to be implemented to curb their spread.

28 In South Africa, commercial forestry and agroforestry have played a major role in the introduction  
29 and spread of particularly woody invasive alien plant species. According to van Wilgen et al  
30 (2001), the majority of invasive species are woody. Most of these species are economically viable,  
31 but ecologically notorious. These include *Pinus* spp (*Pinus patula*, *P. elliottii*, *P. radiata*, *P. taeda*,  
32 and *P. pinaster*) *Eucalyptus grandis* spp. and Wattle spp (*Acacia baileyana*, *A. dealbata* & *A.*  
33 *mearnsii* ) that have spread beyond the boundaries of commercial forestry (De Wit et al. 2001,  
34 Richardson et al. 2015). The financial gains realised from these species make them a conflict of  
35 interest species in South Africa. Particularly, the Australian Acacia (wattle) species have long been  
36 a major invading species in South Africa, shortly following their introduction. According to  
37 Richardson et al. (2011), there are about 70 different wattle species which have been introduced  
38 into South Africa, mostly during the mid-19<sup>th</sup> century. By 1996, Le Maitre et al. (2000) estimated  
39 Australian Acacia to have invaded approximately 630 000 condensed ha, thus listing it as one of  
40 South Africa's worst invaders. The latest estimates from Kotzé et al. (2010), show that *A. mearnsii*,  
41 *A. dealbata* and *A. decurrens*, (Wattle) stands have increased by an estimated 92% (Van Wilgen  
42 et al. 2011). Additionally, Kotzé et al. (2010) noted that wattle predominately invades the fynbos  
43 and grassland regions in South Africa. Due to the ecological significance of Fynbos  
44 internationally, there has been a strong research focus on the impacts of wattle invasion in this  
45 biome as compared to other biomes such as the grassland biome. This calls for further investigation  
46 into the possible restoration efforts as well as increased investment into the control of wattle

47 invasion, particularly in grasslands. As a result, in an effort to curb the spread of invasive species,  
48 by 2008 the South African government had invested over R3.2 billion (van Wilgen et al. 2012). A  
49 large portion of these funds were invested into wattle species (van Wilgen et al. 2012). The high  
50 investment into the control of wattle species warrants the need for the quantification of the impacts  
51 of wattle, and the effectiveness of their control efforts.

52 Traditionally, research on invasive alien species has focused on the characteristics of invasion by  
53 the alien invasive species (Levine et al. 2003, Gaertner et al. 2009, Vilà et al. 2010). These include  
54 mode of dispersal, drivers of spread, and other characteristics determining the invasiveness of the  
55 invading species (Rejmánek and Richardson 1996, Mack et al. 2003, Pyšek et al. 2011). Less focus  
56 has been directed towards the quantification of the ecological benefits of restoration, which is  
57 critical at both community and at regional scales. An understanding of the impacts of wattle  
58 invasion on native plant diversity as well as a quantification of the gains accrued, following  
59 successful restoration are critical for sustainable natural resource management. However, there is  
60 a limited number of studies that investigate the costs and benefits of IAPs (Le Maitre et al. 2002,  
61 Pejchar and Mooney 2009).

62 Meanwhile, Gordon (1998) and Hejda et al. (2009), attest to the importance of comparative studies  
63 that investigate the impacts of IAPs across invaded and uninvaded plots, so as to identify their  
64 impact on native species. In a landscape assessment of the impacts of 13 different invasive species,  
65 Hejda et al. (2009) notes that at a community level, the different invasive alien species have  
66 different impacts on native diversity. This implies that focusing on species-specific impacts is  
67 critical in fully assessing the impacts of IAPs specifically at a landscape scale. Thus, investigation  
68 into species-specific impacts will result in better-informed decision-making, improved land  
69 management and draw major contribution into conservation ecology.



70 Various approaches have been adopted to assess the impact invading species have on biodiversity  
71 at various spatial scales. Specifically, ground based surveys are the most accurate method of  
72 gathering data on the spatial pattern of diversity and how its impacted by invasive species  
73 (Gillespie et al. 2008). However, such research approaches require specialised skills and can be  
74 time consuming. Particularly at a regional scale, the exhaustive nature of traditional ecological  
75 methods make them near impossible to apply (Carlson et al. 1990, Heywood and Watson 1995,  
76 Nagendra 2001, Gillespie et al. 2008). In addressing the scale and time constraints of traditional  
77 methods, remote sensing has made significant contributions into the biodiversity assessment  
78 globally, although it still remains underutilised (Pettorelli et al. 2014). Thus, it remains an area for  
79 further investigation. Remote sensing of species diversity follows two main approaches, direct and  
80 indirect approaches. Direct measurement of diversity involves the identification of species, and  
81 land cover types (Gillespie et al. 2008). Alternatively, indirect methods measure species diversity  
82 using diversity proxies. Both techniques provide significant contribution to conservation planning.  
83 Direct approach however requires high resolution image data, which can be costly. On the other  
84 hand, the use of diversity proxies equally as valuable can be estimated with the use of cheaper  
85 satellite imagery at a lower resolution (Rocchini et al. 2010). However, few studies have applied  
86 remote sensing to investigate the implications of landscape resource management on biodiversity  
87 to inform conservation ecology using diversity proxies.

88 Remotely sensed data derivatives, such as vegetation indices allow for improved mapping of  
89 species diversity. NDVI and SR are some of the more commonly used vegetation indices in  
90 characterising various vegetation components including species diversity (Rondeaux et al. 1996,  
91 Fairbanks and McGwire 2004, Pettorelli et al. 2005). The energy species relationships drive the  
92 correlation of vegetation indices and diversity, thus allowing for vegetation studies to utilise  
93 remotely sensed data for ecological studies (Currie 1991). At local scales, the energy species

94 relationships are hump shaped with species richness increasing at low to moderate energy levels,  
95 which then decrease at high energy levels. The relationship between species diversity and energy  
96 (a term used inter-changeably with net productivity) can be applied in conservation (Phillips et al.  
97 2010). However, Phillips et al. (2010) further argues that the discrepancies in the temporal  
98 application of the species energy relationships are in need for further research. Nevertheless,  
99 several studies have investigated and established this relationship, more specifically with  
100 technological advances in space borne remote sensing allowing further investigation into the  
101 energy-species relationship. For instance, Bawa et al. (2002) utilised Indian Remote Sensing (IRS)  
102 satellite imagery to characterise areas of high and low plant species diversity through modelling  
103 Shannon Wiener's diversity index. Their study demonstrated a strong positive correlation between  
104 NDVI and species diversity in a tropical ecosystem. Other studies showing positive correlation  
105 between vegetation indices and diversity indices include (Diker et al. (2004), Feeley et al. (2005),  
106 Gillespie (2005), Cayuela et al. (2006), Dogan and Dogan (2006), Levin et al. (2007), Saatchi et  
107 al. (2008)) and (Oldeland et al. (2010)), using broad band and hyperspectral data sets

108 Diker et al. (2004), in investigating the relationship between remotely sensed data, agricultural  
109 yield and the crop species diversity, found a positive correlation between both crop yield and crop  
110 species diversity using Shannon Wiener's index with NDVI. Feeley et al. (2005) quantified the  
111 species composition of a dry forest using Normalized Difference Vegetation Index (NDVI),  
112 Infrared Index (IRI), and Mid-Infrared Index (MIRI) derived from Landsat ETM+. Their results  
113 suggest that satellite based remotely sensed data offers reliable estimates of the spatial distribution  
114 of plant species diversity.

115 To date, the diversity assessments studies have been using Spot, Landsat 7 and IRS among other  
116 multispectral sensors, which, do not boast of the same spectral resolution as the new age generation

117 of space borne sensors. One such sensor is the recently launched freely available Sentinel-2 MSI  
118 with three red edge bands and two NIR (near infrared) bands, which has a potential of resulting in  
119 improved accuracies. The previously used sensors do not have the same spectral resolution as new  
120 sensors, specifically the red edge region that is particularly useful in vegetation mapping. Higher  
121 spectral resolution of Sentinel-2 MSI is invaluable in data retrieval. Sentinel-2 MSI offers a  
122 wideswath combined with high spectral and spatial resolution offering an invaluable contribution  
123 in the investigation and assessment of vegetation response to disturbance.

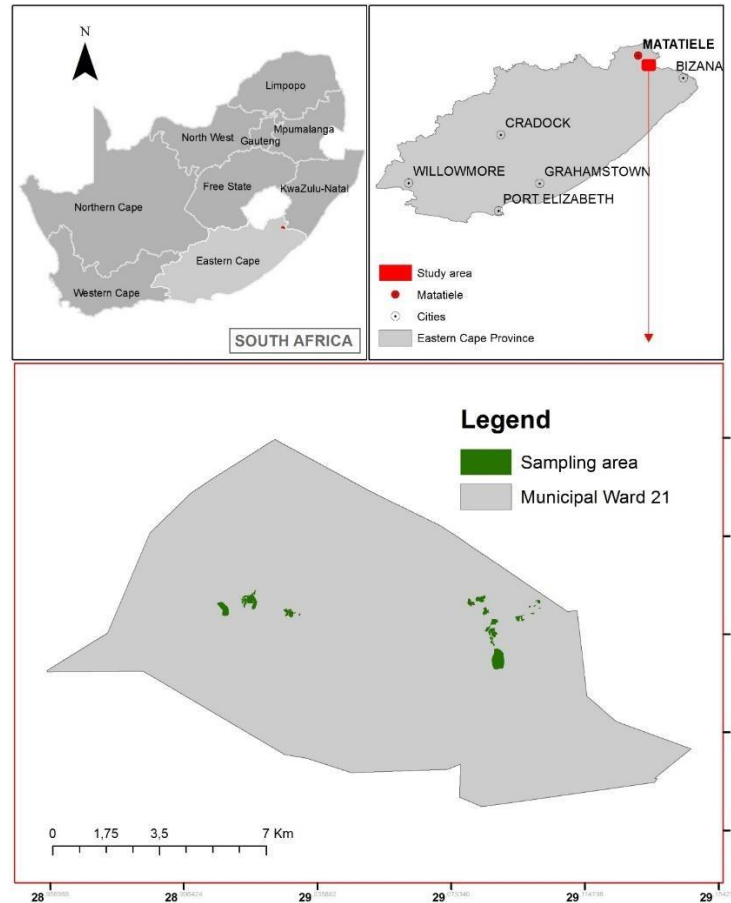
124 This study sought to investigate the applicability of Sentinel-2 MSI derived data to assess grass  
125 species diversity across different levels of wattle invasion in an alpine grassland. Specifically, this  
126 study investigated 1) the variability in species diversity across the uninvaded, moderately invaded,  
127 and heavily invaded alpine grasslands using indices derived from Sentinel-2 bands and 2), to  
128 evaluate the spectral variables that best predict species diversity across the three invasion levels.  
129 It is perceived that this information will ultimately provide insights into the impacts of wattle  
130 invasion and clearing on grass species diversity on native grass species.

131

### 132 **3.3. Methodology**

133

1 This study was conducted in two rural villages located within the Matatiele local municipality,  
2 Eastern Cape Province South Africa (Figure 3.1). Subsistence farming is a common practice  
in  
3 the area, including cattle, sheep and maize farming. Both areas have extensive levels of wattle  
4 infestation, which has negative effects on the natural resources in the area and livelihoods of  
the  
5 residents. The study area was selected due to the extensive level of wattle infestation in the  
area  
6 as well as the restoration effort that has been undertaken in the area to allow for comparative  
7 analysis. The study area falls within the alpine and sub-alpine grassland regions (south of  
8 Drakensberg), and forms part of the largest biome in South Africa (grassland biome). The area  
9 is characterised by summer rainfalls and cold winters. Maximum temperatures in winter can  
10 drop to as low as 10<sup>0</sup>C. As a result, frost is a common occurrence in the area.



1

2 Figure 3.7. Sampling points are highlighted in red in Matatiele, Eastern Cape province, South  
 3 Africa,

4

5 **3.3.1. Field data collection and processing**

6 A stratified random sampling approach was used in this study. The study area was split into four  
 7 strata, which were wattle cleared, moderately invaded and uninvaded. Wattle invaded and  
 8 uninvaded strata we onscreen digitised on the Google Earth platform, while the wattle cleared strata  
 9 was based on supplied data from restoration conducted by Conservation South Africa. The  
 10 different levels of wattle invasion were determined using ground canopy cover of *Acacia*  
 11 *baileyana*, *A. dealbata* & *A. mearnsii* found in the study area. Heavily invaded plots had full canopy  
 12 cover while moderately invaded sites had patches of wattle invasion. In the cleared sites, wattle

13 was removed between the periods of 2013 and 2014, while uninvaded sites are those that had no  
 14 history of wattle invasion. Random sampling points were generated within each stratum using the  
 15 hawths analysis tool in ArcGIS®. A hand held GPS device was then used to navigate to these  
 16 points. These points were then used as the centre points of the quadrats where species richness data  
 17 was collected. The size of these quadrats was 0.5m by 0.5m. Within each quadrat, all the grass  
 18 species and their relative abundance were identified and recorded (forbs and sedges were  
 19 excluded). The points were then overlaid with a 10m by 10m grid in relation to the 10m spatial  
 20 resolution of Sentinel 2 MSI's visible section bands. The resampling to a 10m by 10m grid size  
 21 was conducted to avoid spatial autocorrelation issues. Sampling points that fell within the same  
 22 10m by 10m grid were averaged and the centre co-ordinates of these grids was used for further  
 23 analysis. Following the resampling procedure, a total 182 points remained. The species richness  
 24 and diversity was used to estimate species richness and diversity within the 10m sampling plot.

25

26 **3.3.2. Assessing grass species diversity**

27 To assess the impact of invasion on grass species diversity, species richness, Shannon Wiener's  
 28 and Simpson ecological diversity indices were calculated for each plot. Species richness is the total  
 29 number of species for the entire treatment. The ecological diversity indices were computed based  
 30 on the following equations:

31 
$$\text{Shannon Winer } H = \sum_{i=1}^s - (P_i * \ln P_i) \quad \text{Equation 1.}$$

32 
$$\text{Simpson } D = 1 - \sum_{i=1}^s P_i^2 \quad \text{Equation 2.}$$

33  
 34 Where  $P_i$  is the proportion of one particular species to the total number of species and  $S$  being  
 35 the total number of species. In each of the quadrats, the diversity (Simpson and Shannon Wiener)  
 36 was computed across the four levels of wattle infestations.  
 37  
 38

39

40

### **3.3.3 Remotely sensed variables**

41

A Sentinel-2 MSI image with minimal cloud interference covering the study areas was selected from the internet (<http://earthexplorer.usgs.gov/>) and used in this study. The satellite image was pre-processed and atmospheric correction was conducted using the Semi-Automatic Classification Plugin in Quantum GIS version 2.18.3. Prior to the analysis, the Sentinel-2 MSI wavebands B5, B6, B7, B8a, B9, B11 and B12 were resampled using the constant ground Sampling Distance of 10m derived from the visible bands (B2 B3 B4 and B8). A point map generated from the 10m sampling plots was overlaid with Sentinel 2 MSI's wavebands, to extract spectral data used in this study. The image was then used to calculate the NDVI and simple ratio vegetation indices using all possible band combinations.

50

51

## **3.4. Statistical analysis**

52

53

### **3.4.1. Exploratory data analysis**

54

To quantify the impacts of wattle invasion on grassland species diversity, exploratory data analysis was conducted prior to confirmatory statistical analysis in SPSS. Under the exploratory data analysis, Kolmogorov-Smirnov normality test was conducted to evaluate whether the data (species richness, Shannon Wiener's and Simpson's diversity indices) deviated significantly ( $\alpha = 0.05$ ) from the normal distribution. Considering the data did not significantly deviate from the normal distribution curve, the diversity variables were further subjected to a One Way Analysis of variance (ANOVA). This was conducted to establish whether there were significant differences in grass species diversity across the different levels of wattle invasion. The ANOVA test was followed by a LSD post-hoc test to assess difference within treatments.

62

63

64 **3.4.2. Predicting species diversity using remotely sensed data and partial least squares**  
65 **regression**

66 To predict the grass species diversity, namely, species richness, Shannon Wiener and Simpson’s  
67 diversity indices, partial least squares regression with leave one out cross validation was used. The  
68 accuracy and performance of the derived PLSR model was evaluated using the relative root mean  
69 squared error (rRMSE) and the coefficient of determination ( $R^2$ ). All this was conducted in R  
70 statistical software.

71 The procedure followed in identifying optimal variables for accurately predicting grass species  
72 diversity is outlined in Table 3.1. In the first stage, Sentinel-2 MSI spectral bands, were used to  
73 predict species richness, Shannon Wiener Diversity index and Simpson diversity index. In the  
74 second stage of analysis, vegetation indices, namely, NDVI and Simple ratio were used to predict  
75 grass species diversity. In the third stage of analysis, a combination of the best performing spectral  
76 variables, bands and vegetation indices were used to predict grass species diversity. The accuracies  
77 derived in characterising grass species diversity based on the three- ecological diversity indices  
78 were compared across different levels of wattle invasion.

79

80

81

82

83 1 Table 3.3. Sentinel-2 MS spectral bands and vegetation indices used at the different stages of 2 the  
84 analysis.

Stage Analysis	Variable	List of variables
I	Raw Bands	Visible, Red Edge and Near Infrared and SWIR n=10
II	Vegetation indices	Normalised Difference Vegetation Index: NDVIs (n >100) Simple Ratio: SRs (n>100)



85

86

### 87 **3.5. Results**

#### 88 **3.5.1. Statistical analysis**

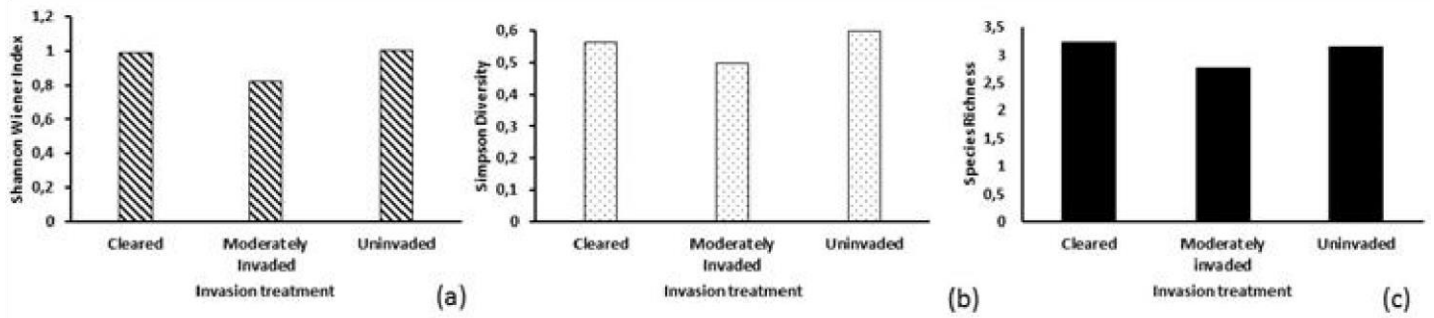
89 An Analysis of Variance (ANOVA) was conducted to compare means of grass species diversity  
90 across the different levels of wattle invasion. The ANOVA results show that there were significant  
91 differences ( $p < 0.05$ ) in grass species diversity across the different levels of wattle infestation

92 (Table 3.2) based on the species richness, Shannon Wiener and Simpson's diversity indices. Figure  
93 3.2 illustrates significant differences in grass species diversity based on species richness, Shannon

94 Wiener and Simpson's diversity indices across the four levels of wattle invasion. Species richness,  
95 which is the total number of species in each treatment, is highest in the cleared plot with a mean  
96 species richness of 3.24. The moderately invaded plot had a mean of 2.76. The control treatment  
97 (uninvaded plot) had a mean of 3.14 species (Figure 3.2 (a)). Based on the Shannon Wiener  
98 diversity index, the cleared treatment had an index of 0.99 and 1 for the uninvaded treatment.

99 While the moderately invaded treatment had an index of 0.82. When using the Simpson's diversity  
100 index, grass species diversity was highest for the uninvaded treatment 0.66 0.56 for the cleared  
101 treatment and was 0.5 for the moderately invaded plot (figure 3.2b).

102 1



103  
104

105 Figure 3.8. Biodiversity variables with mean Shannon Wiener (a) Simpson’s diversity indices  
106 (b) and species richness (c)  
107

108 Table 3.4. Analysis of Variances across the different levels of wattle invasion

Diversity variables	df	F	Sig.
Simpson	2	4.313	0.02
Shannon Wiener	2	4.961	0.01
Species Richness	2	4.111	0.02

109

110 Subsequently, a least significant difference (LSD) Post Hoc analysis was conducted to ascertain  
 111 differences between pairs of treatments. The LSD test showed that the grass species diversity in.  
 112 Based on Simpson’s diversity there were no significant differences between the cleared and  
 113 moderately invaded ( $p = 0.125$ ) and uninvaded treatments ( $p = 0.644$ ). Grass species diversity  
 114 based on the Simpson diversity index in the moderately invaded site was significantly different  
 115 from that of the uninvaded treatment ( $p = 0.013$ ).

116 The LSD post hoc test showed that there were significant differences in grass species diversity  
 117 based on Shannon Wiener diversity index between moderately invaded and cleared ( $p=0.028$ ) and  
 118 moderately invaded and uninvaded ( $p=0.014$ ). There were no significant between cleared and  
 119 uninvaded treatment. A similar trend was observed on species richness data there were no  
 120 significant difference between uninvaded and cleared treatment ( $p=0.841$ ). While Moderately

invaded had a significantly lower number of species compared to the cleared treatment ( $p=0.019$ ) and uninvaded ( $p=0.036$ ).

Table 3.5. Differences between pairs of wattle invasion treatments based on LSD Post Hoc test

Simpson

Cleared			
Moderately invaded	0.125		
Uninvaded	0.644	0.013	
	Cleared	Moderately Invaded	Uninvaded

Shannon Wiener

Cleared			
Moderately invaded	0.028		
Uninvaded	0.976	0.014	
	Cleared	Moderately Invaded	Uninvaded

Species Richness

Cleared			
Moderately invaded	0.019		
Uninvaded	0.841	0.036	
	Cleared	Moderately Invaded	Uninvaded

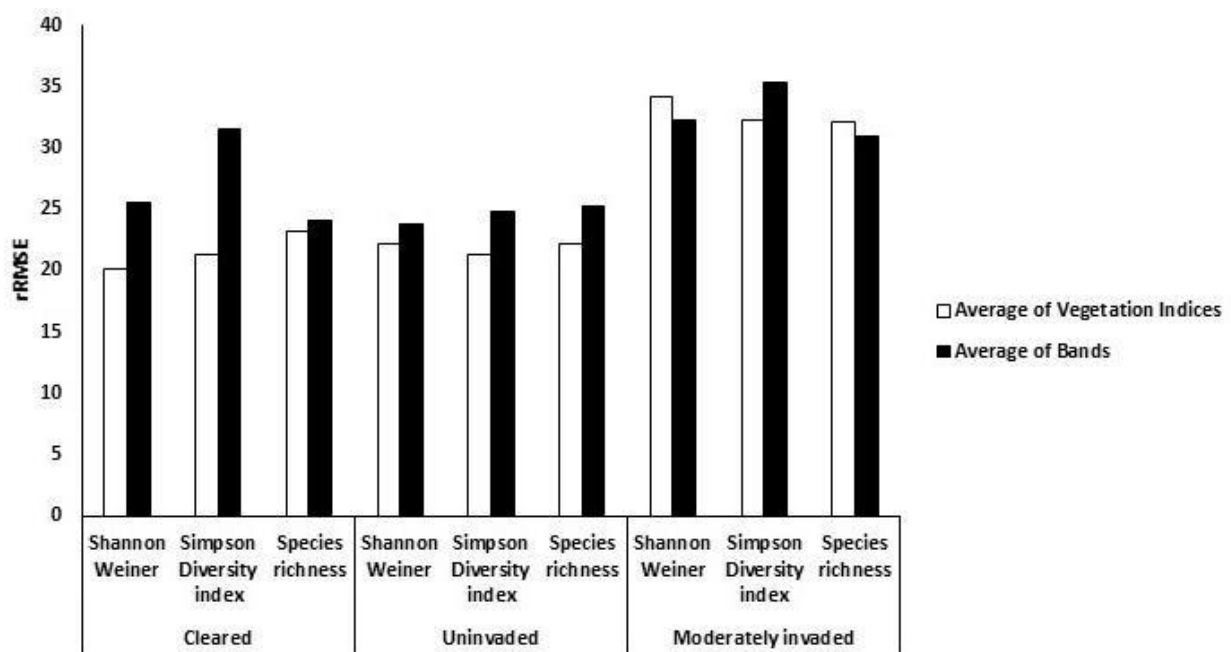
\* Note cells highlighted in dark grey represent significant differences ( $\alpha =0.05$ ).

### 3.5.2. Modelling grass species diversity using spectral data

PLSR algorithm was used to determine which variables optimally estimated grass species diversity across the different levels of wattle invasion. Figure 4 shows a general trend where Sentinel-2 MSI raw spectral bands had a high rRMSE compared to the vegetation indices simple ratio and NDVI.

The performance of the developed models varied with the treatments and with ecological diversity

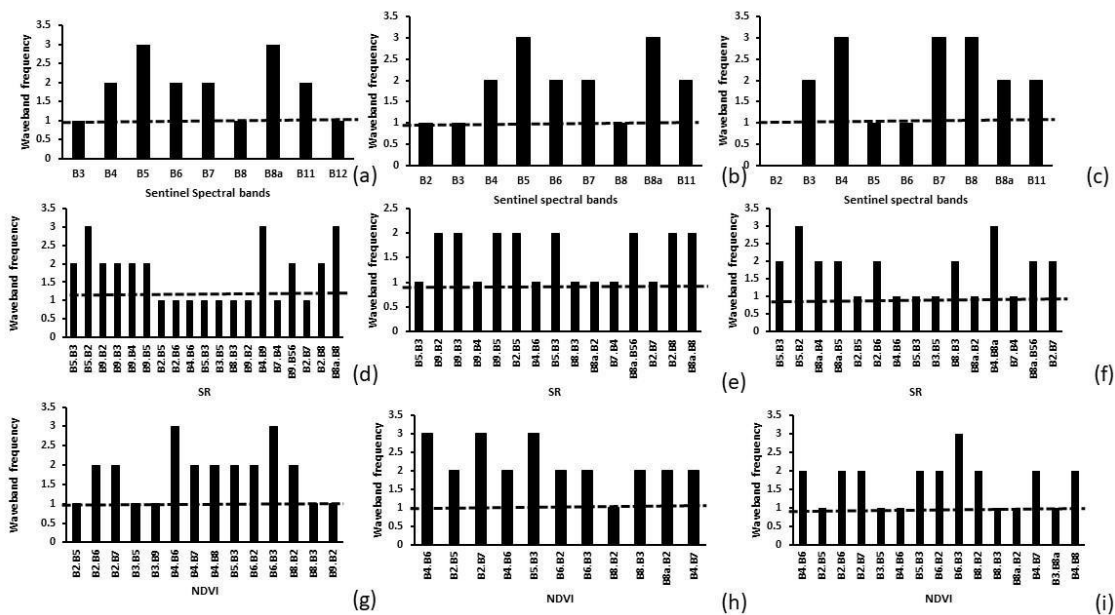
137 index. In the cleared treatment, for Shannon Wiener’s diversity index, the model yielded a lower  
 138 rRMSE of 20.16 % for vegetation indices while it yielded 25.53% for the raw spectral bands  
 139 respectively. While an rRMSE of 21.25% and 31.56 % was achieved for VI and spectral bands  
 140 respectively using Simpson’s diversity index. Finally grass species richness yielded an rRMSE of  
 141 23.13 % for VI and 24.15 % for raw spectral bands. For the uninvaded treatment, the Shannon  
 142 Wiener’s diversity index the model yielded an rRMSE of 22.15 % and 23.8 % for the vegetation  
 143 indices, and raw spectral bands. While an rRMSE of 21.25 % and 24.75 % was achieved for VI  
 144 and spectral bands, respectively using Simpson’s diversity index. For grass species, diversity  
 145 yielded an of 22.25 % for VI and 25.24 % for raw spectral bands. Finally, for the moderately  
 146 invaded treatment the highest rRMSE was realised with spectral band than the vegetation indices  
 147 for this treatment (Figure 3.3).



148 Figure 3.9. Performance of Sentinel-2 MSI variables in charactering grass diversity variables.  
 149  
 150

151 Figure 4 shows the variable importance (VIP) score frequencies of Sentinel-2 MSI spectral bands,  
 152 derived NDVI and SR vegetation indices in optimally characterising grass species diversity across

153 the three treatments of wattle invasion. Sentinel-2 MSI spectral variables that have VIP scores  
 154 above 1 were regarded as the most optimal variables for characterising grass species diversity. For  
 155 the raw spectral bands, the red-edge bands (B3, B4, B5, B6, B7, B8a,B11) had the highest  
 156 frequencies of VIP scores across the three treatments. While for the NDVI, based models, the band  
 157 combination with high frequencies, include B2.B6, B2, B7, B5.B3, B6.B2, B6.B2 and B6.B3. for  
 158 detailed bands see fig4. (d-f). Lastly, for the SR derived models B5,B2, B5.B3 and B8a.B2 band  
 159 combinations were some of the band combination that were considered the most frequent.



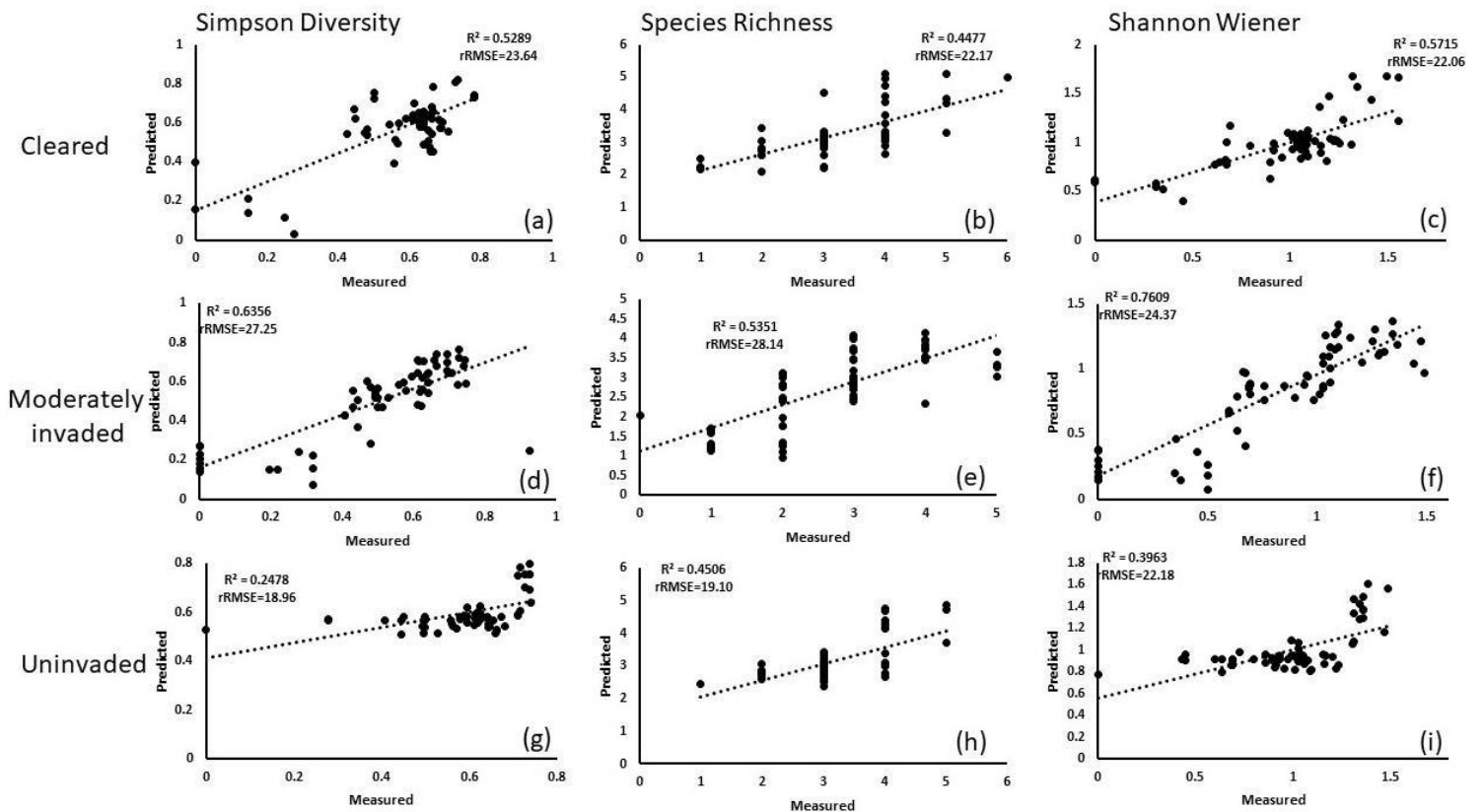
160  
 161 Figure 3.10. VIP scores for the Sentinel-2 MSI derived data variables obtained for characterising  
 162 grass species diversity using (a, d & g) Simpson's diversity index, (b, e & h) Shannon Wiener's  
 163 diversity index and c, f, & i) and species richness from raw spectral bands, the simple ratio  
 164 vegetation index and species richness.

165  
 166  
 167 In evaluating grass species diversity, the results show that the PLSR model estimated grass species  
 168 diversity indices optimally when using a combination of raw spectral bands and derived vegetation  
 169 indices. The developed PLSR models for species richness had  $R^2$  values of 0.54, 0.45 and 0.45 for  
 170 the moderately invaded, cleared and uninvaded treatments respectively (figure 3.5 a-c). Simpson's  
 171 diversity index model had  $R^2$  values of 0.64, 0.53 and 0.25 for the moderately invaded, cleared and

172 uninvaded plots respectively (figure 3.5 d-f). The Shannon Wiener's diversity index models had  
173  $R^2$  values of 0.76, 0.57 and 0.40 for the moderately invaded, cleared and uninvaded treatments  
174 respectively (Figure 3.5 g-h).

175 Shannon Wiener's diversity index was estimated using remotely sensed data with an rRMSE of  
176 18.86, 23.79 and 20.29 for the cleared, moderately invaded and uninvaded. While for Simpson's

1 diversity index an rRMSE of 19.91, 26.98 and 17.11 was achieved. In addition, grass species  
 2 richness was predicted with an rRMSE of 17.95, 24.84 and 20.1 (figure 3.5). Overall, Shannon  
 3 Wiener's diversity index was optimally characterised with the lowest mean rRMSE (figure 3.5). 4  
 The variables that optimally characterised Shannon Wiener's diversity index were then selected 5  
 and used in the succeeding stage of analysis.



6

7 Figure 3.11. Diversity variables measured versus predicted for the different levels of wattle  
 8 invasion. With rRMSE and RMSE for each of the predicted variables. Predicted grass diversity  
 9 variables are Species richness for moderately invaded (a), cleared (b) uninvaded (c) Simpson 10  
 diversity index for moderately invaded (d) cleared (e) and uninvaded (f). Shannon Wiener index 11  
 for moderately invaded (g) cleared (h) and uninvaded (i).

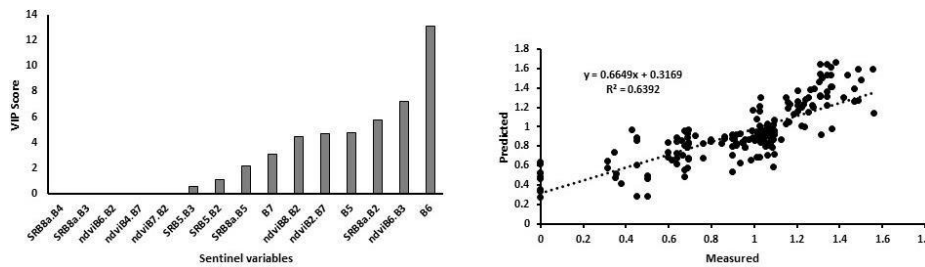
12

13 The most optimal variables in characterising grass species diversity using Shannon Wiener's  
 14 diversity index were identified by the frequency across the different levels of wattle invasion

15 illustrated in Figure 3.6 (a). Specifically, Bands 5, 6 and NDVI (B8/B2), had a high frequency



1 when characterising grass species diversity across the different levels of wattle invasion. The  
 2 selected remote sensed variables (Figure 3.6 (a)) were then combined and used to predict grass  
 3 species diversity across the different levels of wattle invasion combined (pooled). Figure 3.6 (b)  
 4 illustrates the final model for predicting grass species diversity. The developed model for  
 5 predicting Shannon Wiener's diversity index for grasses was predicted with an RMSE of 0.214  
 6 and co efficient of determent value of 0.64.



7  
 8 Figure 3.12. (a) Best performing remotely sensed variables for estimating grass species diversity  
 9 based on Shannon Wiener diversity index pooled for all treatments and (b) the measured versus  
 10 predicted grass species diversity based on Shannon Wiener index across all levels of wattle  
 11 invasion.

### 14 3.6. Discussion

15  
 16 The application of remote sensing to restoration ecology and rangeland management has been  
 17 limited for a while. This is mainly due to the unavailability of sensors with high spectral and spatial  
 18 resolution. Therefore, this study sought to investigate the applicability of Sentinel-2 MS derived  
 19 data to assess grass species diversity across different levels of wattle invasion in an alpine  
 20 grassland.

#### 21 3.6.1. Characterising grass species diversity using remotely sensed data

22

23 The results of this study showed that Sentinel-2 MS bands 5 and 6 together with NDVI, based on  
24 band 8a and 2 where Band 8 is in the near infrared region of the electromagnetic spectrum (EM)  
25 and band 2 in the blue region of the EM, are important in estimating grass species diversity. Bands  
26 5 and 6 are both in the red edge region of the EM. Specifically, Bands 5 and 6 are sensitive to  
27 slight changes in reflectance, which explains their importance in the developed model. The  
28 reflectance of vegetation in the NIR (band 8) has been shown to be important in vegetation  
29 mapping, due to the higher reflectance of vegetation in this region of the electromagnetic spectrum.  
30 The red edge and NIR bands from Sentinel-2 MSI offer reliable predictors of grass species  
31 diversity in the study area. There is a strong body of literature supporting the use of spectral  
32 variable as predictors of species diversity. Specifically, Gillespie (2005) suggests that the  
33 relationship between NDVI and species diversity is based on photo synthetically active radiation  
34 (PAR) that is used in the net primary productivity. Although there is also an argument that the  
35 strength of species diversity and NDVI relationship may vary with season, vegetation type and is  
36 species-specific. The red edge band based variable combined with NDVI enhances the accuracy  
37 of the predictor variables. This is evident from the frequency of variable importance across  
38 different levels of wattle invasion. This is further supported by Baret and Guyot (1991) and (Levin  
39 et al. (2007)).

40

### 41 **3.6.2. The impacts of wattle invasion on native grass species diversity**

42

43 Both Shannon's and Simpson's diversity indices take into consideration species evenness and  
44 richness. Simpson's diversity index is however more sensitive to dominant species, while the

45 Shannon Wiener's diversity index is more sensitive to rare species (Boyle et al. 1990). Based on  
46 the observation of this study, dominance of a single species was mainly a result of disturbance.  
47 Unpalatable species such as *Eragrostis plana* and *E. curvula* were dominant across all treatments,  
48 thus lowering the grazing capacity in the study area. These species are unfavourable in a rangeland  
49 system. However, palatable species such as *Themeda triandra* and *Hyparrhenia Hirta* were rare  
50 in the uninvaded treatment and absent in the invade treatments. This explains why in the present  
51 study, Simpson and Shannon's diversity indices had conflicting results in terms of estimating grass  
52 species diversity in invaded plots using remotely sensed data. With Simpson's diversity index  
53 estimating the highest value for the heavily invaded treatment, whereas the opposite is measured  
54 using Shannon's Wiener diversity index for the same treatment (figure 2). As a result, Nagendra  
55 (2002) emphasises caution when selecting which diversity index is to be applied. In disturbed  
56 rangeland, there are rare palatable grass species that rangeland ecologists aim to conserve and  
57 promote, including *Themeda triandra*.

58 Nagendra (2002) further suggests the use of Simpson's index in treatments where conservation  
59 efforts are concentrated towards a single dominant species. This is not the case for this study area,  
60 where conservation efforts are focused on restoring grass species diversity and promoting palatable  
61 (decreaser) species, which are rare in the current study. Divergence in ranking by Shannon Wiener  
62 and Simpson's diversity indices is uncommon, but not ruled out. As a result, few studies have  
63 emphasised the importance of electing the appropriate diversity index to meet specific diversity  
64 goals (Nagendra 2002).

65 This study is at a small scale, however, the results were able to detect the decline of grass species  
66 diversity and richness at both moderately invaded sites and heavily invaded sites. Even with the  
67 clearing of wattle species, this study was able to show species recovery in less than three years

68 following restoration. There are several factors that can be attributed to the decline in species  
69 diversity, particularly competition for resources. At smaller scales, the decline in diversity as a  
70 result of invasion is even more intense (Gaertner et al. 2009).

71 Wattle species are notorious for altering ecosystem processes, which, ultimately leads to changes  
72 in community structure, including species composition and species diversity. Wattle species are  
73 nitrogen fixing, thus they alter ecosystem function by changing nitrogen availability and nutrient  
74 cycling (Garner 2007, Gaertner et al. 2009). Tree grass interactions are predominantly guided by  
75 facilitation and competition (Scholes and Archer 1997). At dense canopies, there is strong  
76 competition for light. In the present study, it is evident that in heavily invaded plots, wattle tree  
77 stands shaded the native grass species resulting in lowered species richness and diversity.  
78 However, Levine et al. (2003) argues that there is a need for further research to determine the  
79 drivers of changes in community structure.

80

### 81 **3.7. Conclusions and implications**

82

83 Results of this study showed that Sentinel-2 MS derived variables were able to estimate  
84 biodiversity variables at high accuracies. Specifically, bands 5 and 6 together with NDVI, based  
85 on bands 8 and 2. Finally, Shannon Wiener's diversity index optimally characterises grass species  
86 diversity across the different levels of wattle invasion when compared with Simpson's diversity  
87 index. This study was able to demonstrate the applicability of remotely sensed data in estimating  
88 species diversity in a grassland system invaded by wattle. This ultimately underscores the  
89 applicability of remote sensing in quantifying the costs of wattle invasion and the benefits of its  
90 control. Additionally, this study was able to demonstrate that wattle invasion reduced grass species

91 diversity. We recommend the use of Shannon Wiener's diversity index over Simpson's diversity  
92 index due to the former's sensitivity to rare species, which would be best for the conservation  
93 targets in this disturbed grassland.

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## 4. REVIEW OF OBJECTIVES AND CONCLUSIONS

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## **4.1. Introduction**

This chapter is a synoptic review of the objectives and the major findings as well as a reflection of the main conclusions of this study. The prime objective of this study was to investigate the application of remotely sensed data in monitoring grassland restoration following wattle invasion in a South African Alpine grassland. This overarching objective was achieved through the following specific objectives:

1. To investigate the applicability of Sentinel-2 MSI data in assessing grass species diversity across different levels of wattle invasion in an alpine grassland.
2. To investigate the utility of Sentinel 2 MSI remotely sensed data as a cost-effective and quick assessment technique of the ecological response of native grasses to invasion by wattle species.

### **4.1.1. To investigate the utility of Sentinel 2 MSI remotely sensed data as a cost-effective and quick assessment technique of the ecological response of native grasses to invasion by wattle species.**

Grasslands are the backbone of livestock farming. The implementation of sustainable farming practices leads to increased productivity in grasslands through increasing the grazing capacity of grasslands. These are difficult to implement in a communal grazing systems which is affected by the tragedy of the commons. Overgrazing compounded by other ecological disturbances can severely decrease stocking rates of rangelands. For instance, invasion of grasslands by IAPs may lead to decreased grass productivity. As a result, this study was concerned with assessing the use of Sentinel 2 MSI remotely sensed data as a cost-effective and quick assessment technique of the ecological response of native grasses to invasion by wattle species.

25 The results of this study found that in terms of biomass, there are no significant differences between  
26 cleared and uninvaded plots. Invasion significantly reduced grass AGB. The developed model  
27 found that the most influential variables in estimating biomass were the red-edge based simple  
28 ratio with band combination band 5 and band 2. Ultimately, this study found that Sentinel 2 MSI  
29 offers free reliable data for the prediction of grass AGB. This study underscores the application of  
30 remotely sensed data for the use of monitoring grassland restoration success. Although the results  
31 suggest that sentinel offers an optimal estimation of grass AGB across different levels of wattle  
32 invasion, there is still a need to assess the applicability of remote sensing in assessing grass species  
33 diversity recovery following the clearing of wattle.

34

#### 35 **4.1.2 To investigate the applicability of Sentinel-2 MSI data in assessing grass species** 36 **diversity across different levels of wattle invasion in an alpine grassland.**

37

38 Invasive alien species are the second largest threat to species diversity globally, as a result there is  
39 an increased need to invest more in the monitoring of species diversity loss following invasion and  
40 the subsequent gain following restoration. Research on monitoring species recovery has previously  
41 been limited by poor spatial representation of restoration progress. As a result, this study sort to  
42 assess the application of Sentinel 2 MSI in monitoring grass species diversity across different  
43 levels of wattle invasion in an alpine grassland.

44 This study found that Sentinel-2 MS derived data optimally predicted native grass species using  
45 Shannon Wiener's diversity index. Specifically, bands 5 and 6 together with NDVI, computed  
46 from bands 8 and Band 2 were most influential variables in estimating native grass species  
47 diversity using Sentinel 2 MSI. This study demonstrates that Sentinel 2 MSI can predict grass  
48 species diversity at reasonable accuracies. Additionally, the result of the study showed that wattle



49 invasion reduces grasses species richness and diversity, while the clearing of wattle increases grass  
50 species diversity.

51

## 52 **4.2. Conclusions**

53 This study was formulated to investigate the application of remote sensing for monitoring  
54 grassland restoration following wattle invasion in a South African Alpine grassland. This chapter  
55 is interested in reviewing the objectives and highlighting the main conclusions of the research.  
56 The main findings of this study show the Sentinel MSI 2 can be used to monitor grass restoration  
57 projects with reliable accuracies. This shows Sentinel 2 MSI proves to be a cheap and reliable data  
58 source for the monitoring of restoration progress. This study found that Sentinel MSI 2 is able to  
59 predict both grass AGB and native grass species diversity following the clearing of wattle. For  
60 both AGB and grass species diversity the developed model proved that the red edge regions of the  
61 electromagnetic spectrum are crucial in predicting grass variables.

62

## 63 **4.3 Recommendations**

64

65 The finding of this study highlight the importance of the Sentinel 2 MSI and remote sensing in  
66 assessing and monitoring restoration success. The finding of this study present an opportunity for  
67 the application of remote sensing techniques to be applied to inform policy and decision-making.  
68 Based on the findings of this study we recommend restoration success monitoring be conducted as  
69 larger spatial scales. Additionally, future research can investigate the effects of changes in seasons  
70 specifically how this may affect the accuracy of the developed models.

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## 5. REFERENCES

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