Mapping and Modelling above Ground Biomass in a Mountainous Terrain using multi-source remote sensing and environmental data

by

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***Abstract**:*

South African grasslands involve a diverse plant species that makes up the ecosystem but due the disturbances by human alteration, it is very hard to recover from those severe disturbances. In South Africa, the disturbance of grasslands is degradation through the cumulative influence of overgrazing and cultivation of crop in grasslands. In the Free State province, the degradation of grasslands is of vital concern due to the evolving negligence of proper monitoring and maintenance of the environmental and natural resource utilisation. Furthermore, within the mountain environments, grasslands are sources of carbon pool that require careful monitoring and evaluation. Globally, there is a lack of knowledge on the amount of carbon stock in mountainous grasslands. This alone creates huge gaps in knowledge in global carbon cycling. Therefore, the emphasis of this study was to model and map the above-ground grass biomass using a multi-source data in the montane region for the broader and better management of grassland in a protected mountainous park.

The study used Sentinel-2 MSI and Landsat 8 OLI to model and enhance biomass prediction in a mountain. Field-based data points were created to measure biomass on the field across defined plots. Sampling points (based on field-based data points) were used to extract reflectance data from Sentinel-2 and Landsat 8 before and after fire. The regression model used to estimate herbaceous biomass was the random forest (RF), while ANOVA and Spearman Rank correlation was employed to understand variations across two data sets and correlation between environmental drivers and biomass. RF regression model with polynomial pre-processing was adopted, because it is robust and non-parametric. The results show that the R^2 *before fire value differs slightly for the two data sets (Sentinel-2 0.92 and Landsat-8 0.87) whilst the* R^2 *af ter the fire for the two data sets is equal (0.88). The p-value for the two data sets (Sentinel-2 MSI and Landsat 8 OLI) of before and after the fire is* <0.05*, shows that there is a strong correlation between the two data sets and biomass. Biomass did not show any significant difference across Burn Area Index (BAI), dominant grass species and generalized soil types (*$p>0.05$*) when tested with Kruskal-Wallis ANOVA. Finally, sentinel-2 MSI (RF model) and environmental variables is significant and have an operational potential for the estimation of the AGB of herbaceous grass in the mountain region.*

***Key words**: Herbaceous biomass, Random forest, environmental variables, ANOVA, multi-spectra*

DEDICATION

I dedicate this dissertation to my mother (Semela Thobeso Amelia) and my late father (Semela Paseka Joseph), my son (Semela Retshepile Hope), my fiancé Jeremy Jansen and my entire family members.

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DECLARATION OF ORIGINALITY

Student Number: **2009154531**

I **Semela Mathapelo** declare that the mini-dissertation on the topic of *Modelling and mapping the aboveground grass biomass using multi-source data in the Montane region* submitted to the University of the Free State for masters in science for Geography studies is my work and has not been presented or submitted for any other degree at any University. Therefore, it denotes my original work apart from where accurate acknowledgements are made.

SIGNATURE: DATE: 30 November 2020

Student: Miss M Semela

November 2020

This dissertation has been submitted with my approval for examination and as University supervision.

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ACRONYMS

AGB	Above -Ground Biomass
BGB	Below-Ground Biomass
GIS	Geographic Information System
GPS	Global Positioning System
ANOVA	Analysis of variance
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
MODIS	Moderate-Resolution Imaging Spectroradiometer
AVHRR	Advanced Very High Resolution Radiometer
GGHNP	Golden Gate Highlands National Park
RS	Remote Sensing
SPOT	Systeme Pour I 'Observation de la Terre
TM	Thematic Mapper
BAI	Burn Area Index
RADAR	Radio Detection Ranging
LIDAR	Light Detection and Ranging
RF	Random Forest
ESA	European Space Agency
SARs	Synthesis Aperture Radars
NFP	Net Primary Production
VIF	Variables of Importance Factor
ASTER	Advanced Thermal Emissions and Reflection Radom
DEM	Digital Elevation Model
MSI	Multi-Spectral Instrument
NDVI	Normalised Difference Vegetation Index
GDP	Grass Domestic Product
RMSE	Root Mean Square Errors
ANN	Artificial Neural Network
SNR	Signal Noise Radiometri

Chapter 1

Introduction and Motivation

1.1. Introduction

Mountain areas consist of the grasslands that provide not only an ecological subsystem for biodiversity but also integrated economic areas for livelihoods and the development of herders. The mountain regions are home to many floras, including but are not limited to tall grasses, prairies, steppes or short grasses, desert shrublands, shrub woodlands, savannahs, chaparrals, and tundra (Axelrod, 1985). Furthermore, mountain regions also provide habitats for a variety of species that depend on the rangeland for a diverse and wide range of services. These services include; clean air and clean water quality, nature experiences and available spaces and even for all renewable resources such as plants for food, grazing and other forms of low-input industries (Pretty and Bharucha, 2014). However, due to several factors, these services are not provided equally across space in a typical montane environment due to diverse reasons, chief of which is anthropogenic activities. These activities control the distribution of mountainous grassland across space.

Grassland ecosystems are considered either as natural or semi-natural vegetation type. Grasslands occupy over 30% of the earth’ land that is an important component of global terrestrial classification ecosystem, which is estimated to be contributing over 20% in all terrestrial’s total primary productivity (Jin *et al.*, 2014). These ecosystems represent an integration of social and ecological dependends on the disciplinary standpoint. In many countries, grasslands are affected by fire either purposive for the management of the grass in the parks and others due to human activities. Various human activities leading to fire events in a typical grassland most often than not affects the normal cycle and growth pattern of the grasses. These activities include but are not limited to throwing a lit cigarette butt on the ground. Sometimes high temperatures due to climatic changes and environmental impacts from anthropogenic activitiescan cause fires to the herbaceous grass species. These activities either natural or man-made inherently affect the distribution of grass species either in a mountain or lowland environment. This disruption in the distribution of grass species has implications on the above-ground biomass within these environments.

The above-ground biomass (AGB) is defined as every living organic elements that appears on top of soil namely, grass, branches, bark, and vegetation or flora by simple terms. It is the total quality of living biotic creatures in a given part or biome at a (Ryan, 2002.). Due to a rapidly growing population and a deteriorating resource base, sustainable development places greater and conflicting demands on available agricultural resources including grass. One of the major implications of a rapidly growing population is the pressure on available land. With continued and sustained pressure, there is bound to be changes in land use pattern which often reduce the coverage of grassland, this invariably affects above-ground biomass. Above-ground biomass is also connected to various vital factors such as carbon cycle, fuel accumulation and habitats in a terrestrial ecosystem to mention a few. In its role in carbon sequestration, above-ground biomass then becomes a major carbon pool. In a montane environment, above-ground biomass of mountain environment is very significant in global carbon stock.

Two methods that are usually used to estimate the biomass on the above ground. These are direct and indirect sampling methods as according to Gómez *et al*, (2016). The direct method is simply the method that involves harvesting and weighing which is equivalent to estimating the actual biomass of vegetation in quadrats while the indirect methods involve the relationship between the vegetation weight, height and diameter. During data collection, the models focus on specific arrays of measurements and those which do not fall into the classification becomes neglected.Valuation of the above-ground grass biomass using the remote sensing normally practises two approaches (1) empirical method that involve the statistical relationship between ground sites of aboveground biomass coordinated with the spectral bands or other related bands in a remote sensing's image pixels; and (2) procedures of methods that involve the remote sensing data as an inputs to predict aboveground biomass. Empirical methods usually include using a regression relationship between the remotely sensed images and biomass data collected from field trip (Dungan, 1998). Many above-ground biomass (AGB) monitoring and modelling methods on grasslands are characterised into two: ground built and remote sensing approaches. The ground-based approaches are the traditional methods that involve going to the field, cutting the grass (samples) drying it and finally weighing it in the laboratory. This approach is simple, however, it is considered time-consuming, costly and tiring: as a result, it is applicable only for monitoring and modelling small-scaled areas (Xu *et al*., 2008).

Remote sensing data is suitable for land usage and coverage ulterations, mapping and monitoring of vegetation and has a great advantage of covering much broader areas that provides a chance to evaluate biomass (grass) from protected to communal land as compared to that of traditional point-based assessment (Nagendra *et al*, 2013). The remote sensing approach is much improved and highly recommended as the best choice for its large data acquisition. It also has the potential to give cost-effective approaches to map grass groups by decreasing the time and work-intensive field specimen and improves the laboratory analysis that is essential by field-based mapping practices (Lewis *et al.*, 2013). Multispectral and hyperspectral data has been frequently and most effectively used in mapping grass groups (Madugundu, *et al.*, 2008). Mapping grass classes and groups are challenging with multispectral data because they have shortage of appropriate spatial and spectral resolutions (Sibanda *et al.*, 2017), hence, there is the need for a sensor that would provide a suitable spatial and spectral resolution. Multispectral MS) images have high spatial resolution (HSR) and low spectral resolution. The high resolution of multispectral image fusion technology can combine both advantages which are beneficial for accurace classification of features. The availability of newer Earth Observation satellites such as the European Space 126 Agency (ESA) Sentinel series, which are now freely available and operational since 127 2015, offers new opportunities to assess the capabilities of determining AGB of 128 palustrine wetland in temperate and semi-arid grasslands (Li, 2019). The newer Sentinel-2 with landsant-8 sensors are multispectral sensors which helps to obtain more accurate locations and shapes of ground objects and spectral information helps to identify types of features from images that make use of vegetation indices and the red edge (Feng et al., 2020). The use of vegetation indices and the red-edge band of new optical sensors have 101 improved the estimation of wetland and terrestrial AGB, overcoming the saturation 102 effect of higher AGB and dense canopies (Mutanga *et al.*, 2012; Ramoelo *et al.*, 2015; Sibanda *et al.*, 2017). In grasslands, vegetation indices 104 offer the advantage of superseding the influences of soil background, atmospheric 105 composition and the viewing and zenith angle effects while enhancing the vegetation 106 signal, when estimating AGB.

Researches on grasslands aboveground biomass (AGB) monitoring and modelling using the Remote Sensing and GIS techniques has been given more attention lately (Ramoelo et al., 2015: Zolkos *et al.,* 2013: Nuthammachot *et al.,* 2020). The use of hyperspectral and multispectral sensors has greately been extrapolated in estimating the abovegroung biomass globally especially for carbon stock. Globally, there is a lack of knowledge on the amount of carbon stock in mountainous grasslands. This alone creates huge gaps about the knowledge for global carbon cycling. However, estimating the aboveground biomass in Mountain area using this techniques has been slightly or less given attention to especially in the South African context, hence this research's development for mapping and modelling above-ground biomass of montane grasslands using multi-source remotely sensed data. This research will give evidence to the resource managers especially in mountain areas with its different elevations that are difficult to access or are not natural possible to get access to the knowledge about the vulnerable grass species and the extend to which how other environmental variables impact the biomass. This will reinforce the knowledge abouth the biomass and its relationship with the environmental variables that either affect or support it for efficient and sustainable use of the grass resource since it is also an economic booster a in the surrounding areas to the park. Furthermore, this will also support the scientific knowledge of environmental management practices for SANParks and other grobal parks

1.2. Problem statement

One of the important ecosystem amenities given by grasslands is the maintenance of atmospheric composition in form of carbon sequestration. Carbon sequestration is the process through which atmospheric CO_2 is secured in other long-lived carbon (C) pools to prevent accumulation in the atmosphere (Lal, 2008). Sequestration of large quantities of C in grassland soils is very important for maintaining the dynamics of the atmospheric carbon cycle (Fan *et al*., 2008). Whether below or above-ground, the storage of carbon in grasslands is vital to the development of viable plans for mitigating climatic alteration at this scale. Most grasslands, are threatened globally due to various direct and indirect anthropogenic factors such as an increase in the human population, deforestation, over-grazing, fires, and invasive species (Szabó, 2005 and Binggeli, 2003). Figure 1.1, shows the most affected types of grass especially in the mountain areas. Modelling, monitoring and mapping the biomass especially in montain grasslands has become a key issue that has gained attention in the entire world, inorder to maintain, manage, preserve as well as to conserve our natural resources. Due to its significant role in carbon sequestration in such unique environment it is key to ensure that these species are managed in a correct way.

Figure 1.1 Serrated tussock (A) and African lovegrass (B), sourced: https://www.environment.gov.au/biodiversity/invasive/weeds/publications/guidelines/wons/pubs/n-trichotoma.

Pieces of literature showing the reason why grassland ecosystems are exposed to climate change effects, degradation, i.e. droughts that led to natural fire occurrences, invasive species, etc. This condition compromises the above-ground biomass (AGB) of grass ecosystems with confrontational effects on rangelands health, thus causing significant defies on the conservation of biodiversity and the sustenance of human livelihood (Yapp et al, 2010). Therefore, mapping and modelling above-ground biomass of grasslands in mountain area become vital.

1.3. Aim and objectives

This study aims to map and model the above-ground biomass of grasslands in a mountainous terrain using multi-source remotely sensed data.

To achieve the aim of this study, the following objectives were considered.

1. To test and compare the correlation between Sentinel-2 and Landsat-8 for before and after fire with biomass.
2. To model and map the distribution of grass biomass using multi-sourced data.
3. To quantify the influence of different environmental data affecting grass AGB.

1.4. Research Questions

This research presents the following questions:

1. Which data set (sentinel-2 and landsat-8) for before and after fire correlates best with biomass?
2. What model is best suitable for modeling the above ground biomasss of mountainous grassland?
3. How are different environmental variables affecting the montane biomass?

1.5. Study significance and justification

Many researchers have exploited empirical modelling approaches to estimate above-ground biomass globally, with limitations of using field-based methods which is limited to a certain extent especially in rugged and remote terrains such as montane environments. Understanding the distribution and features of the grassland biomass is vital for sustainable ecosystem and its management through its key role such as but not limited to providing habitat for livestock and wildlife and also to inducing the grazing supply forms. Currently, the study on resource management using Remote Sensing and GIS has been given great attention, however, this study will contribute to the methodological evaluation of resource management in protected areas. This study make use of the two multispectral sensors: sentinel 2- MSI and Landsat 8- OLI to check the distribution and the correlation of the grass biomass in the park for sustainable development. Landsat-8 OLI sensor works through push-broom expertise that allows the data procurement with much improved signal-to-noise (SNR) performance and higher radiometric resolution (Dube *et al.*, 2015, Mielke. *et al*, 2014). Sentinel-2 MSI has a huge swath (290 km) with a high return to frequency of 5days periodicity at the equator and systematic attainment of all land sides and coastal seawaters. It is high spatial resolution and accurate geo-location (20 m without Ground control parts (Drusch *et al*. 2012). Burning of biomass is extensively been known as one of the critical factors affecting vegetation sequence and carbon stock globally (Chuvieco 2008; Thonicke *et al*. 2010).

1.6. Study Area

The Golden Gate Highlands National Park (GGHNP) is located in the north-eastern Free State (Figure1.3). The GGHNP is situated in the mountainous region within the grassland biome, 25 Km east of Clarens and 70 km South-east of Bethlehem. It covers the area between 28º27'S and 28º 37'S and between 28º335' E and 28º42' E. The climate of the area can be described as summer rainfall, moderate summers and icy winters. The rainfall period stretches from September to April with a mean yearly rainfall extending from 1,800 mm to 2,000 mm. Summers are cool with the likelihood of thunderstorms; winters are cold with irregular snow, which adds to the scenic beauty of the area. (Grab *et al*. 2011). The Maloti Drakensberg mountain range is one of only five areas in southern Africa where annual rainfall exceeds evaporation rates (Stewart and Mitchell,2018) see Figure1.2.

The GGNHP is characterized by a high diversity of ecosystem with the dominant five grass vegetation types which are classified (Mucina and Rutherford, 2006) as:

1. Eastern Free State sandy grassland;
2. Basotho montane shrublands
3. Northern Drakensberg highlands grassland
4. Drakensberg-Amatole Afromontane fynbos;
5. Lesotho highland basalt

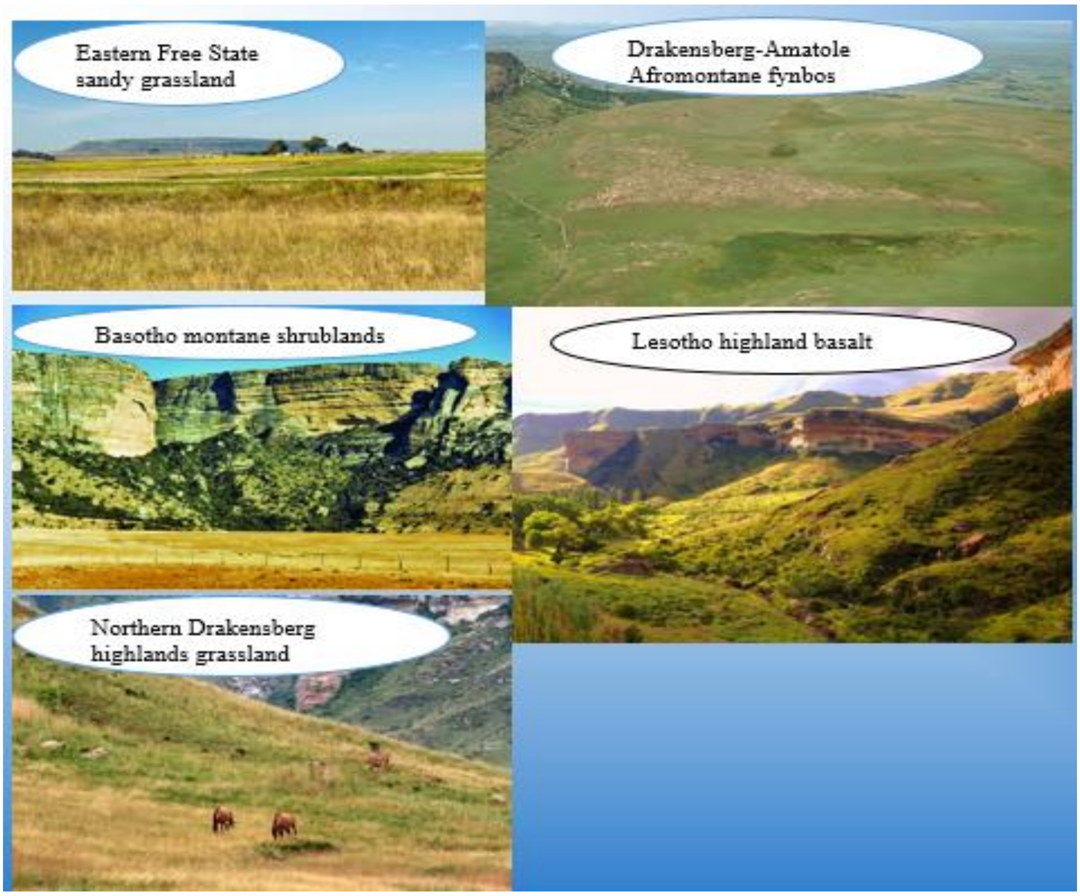


Figure 1.2. The grass Types of the Golden gate national highlands park (GGNHP), according to (Mucina & Rutherford, 2006).

The topography of the area varies (Figure 1.4), with an altitude ranging between 1225 and 3034 m as resulting from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) digital elevation model (DEM).

Grassland are made up of combinations of plants and rising temperatures may cause a change in the relative supremacy of different species in the community. These changes in community structure have been discussed and evaluated relative to climate change by Izaurralde *et al*. (2011). Communal in feeding grasses of lower latitudes, maize, sorghum, sugarcane, fonio, tef, and papyrus.

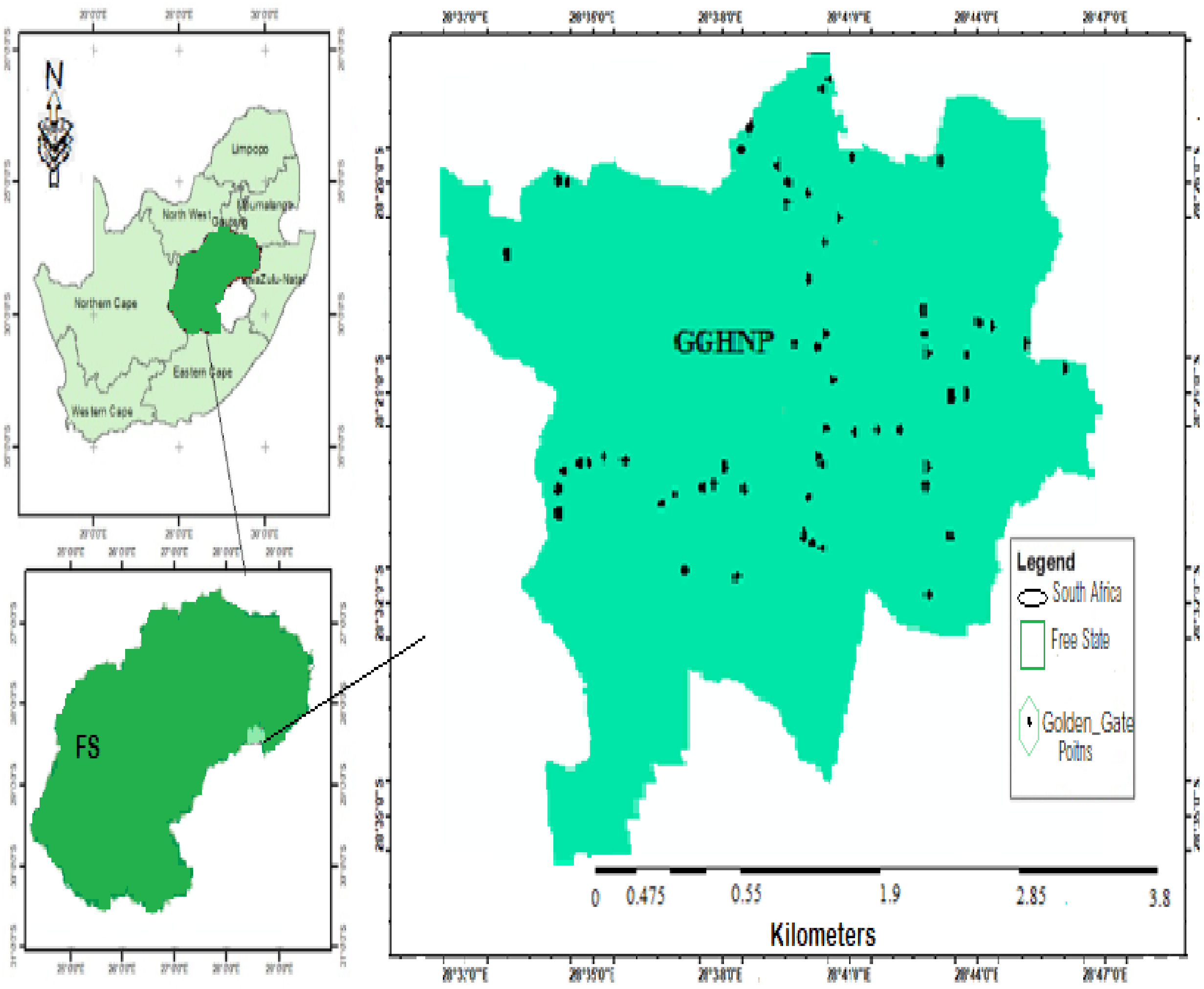


Figure 1.3. Study area.

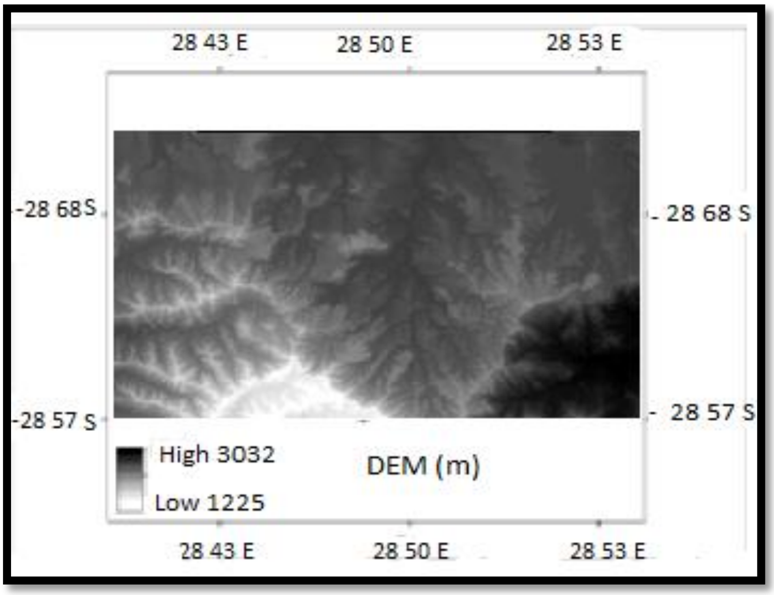


Figure 1.4. Study area with the Altitudinal variation .

1.7. Research Outline

Chapter 1: The direction of the research outlining the background, problem statement, aim and objectives, research queries and the approach of the research.

Chapter 2: Montane Grasslands and Biomass estimations using remote sensing techniques: A review

Chapter 3: Comparison of the Sentinel-2 MSI and Landsat 8 through different algorithms

Chapter 4: Compare the effects of the environmental variables on herbaceous grass species across the topography

Chapter 5: Synthesis and recommendations

1.8. Conclusion

The great improvement in understanding the nexus and distribution of grass biomass to propel good management has been given good attention lately. The use of traditional methods has some pitfalls especially in a larger and mountainous area with a different landscape. Recently a notion of achieving a proper and reliable mapping of the AGB is done through the use of RS and GIS techniques for effective management techniques, especially in high mountainous grassland areas. Therefore, in light of these, this study applies GIS and RS techniques to understand grassland biomass in a montane environment with unique and divergent grass species.

Chapter 2

Literature Review

This chapter is based on:

Semela, M, Olusola, Adelabu S. A, and Ramoelo, A, 2020. manuscript # 20-6298 entitled "MONTANE GRASSLANDS AND BIOMASS ESTIMATIONS USING REMOTE SENSING TECHNIQUES: A REVIEW" which was submitted to the Journal of Mountain Science.

Abstract

Grasslands are the least protected biome across the world and especially in Africa. The range of ecosystem services provided by grassland biomes includes but are not limited to the provision of grazing for herbivores, the land for social interactions, and sequestration of carbon. Carbon sequestration as provided by grasslands ensures the maintenance of atmospheric composition with regards to global warming. Sequestration of large quantities of Carbon (C) in grassland soils is very important as an esteem for maintaining the changing aspects of the atmosphere. Most grasslands are threatened globally due to various direct and indirect anthropogenic factors such as an increase in the human population, deforestation, over-grazing, fires, and invasive species. These anthropogenic factors in light of changing climates are becoming amplified leading to the gradual or total destruction of global grassland communities. These transformations release carbon stocks sequestered in grassland biomes globally leading to the global accumulation of atmospheric carbon (CO_2). Even though several studies have presented carbon loss from various grasslands across the world due to various anthropogenic practices and natural disasters, there is still a gap in accounting for global carbon sink or loss from grassland biomes especially from the grasslands of the montane environments that are largely underrepresented. Mountainous areas are largely inaccessible due to rugged terrains and harsh weather conditions. Hence, this review aims to present approaches to studying biomass in montane grasslands and their challenges. The study concluded that the best approach to biomass estimation in montane grasslands of Africa is in the use of dynamic sensors especially the Radio Detection and Ranging (RADAR) and Light Detection and Ranging (LiDAR). However, the downside for LiDAR is in its acquisition which as of now is still very expensive. The readily alternative is the RADAR fused with multispectral images (RapidEye, Sentinel-2 and Worldview) that can provide the required information on grassland biomass in montane regions.

Key words: *Biomass, Active sensors, montane grasslands, Carbon, Africa, global warming*

2.1. Introduction

Grasslands are found the world over except in Antarctica. Globally, grasslands can be divided into two; temperate and tropical. The temperate grasslands are called by different names; prairies, steppes, velds, pampas. The tropical grasslands are largely referred to as savannas. Grassland biomes occupy about 20% - 40% of the whole land area on earth and they have little or absence of trees (Egoh *et al.*, 2011). From time immemorial, grasslands serve as sources of animal products and also home to indigenous people (Kang *et al*., 2007). Their role in the environment as regards the sustenance of ecosystem services and ground for social interactions for animals is quite remarkable. Ecosystem services explanation by Daily, (1997 p.3)

> *"are the circumstances and procedures through which natural ecosystems, and the species that make them up, sustain and fulfil human life ... In addition to the production of goods, ecosystem services are the authentic life-support functions, such as cleansing, recycling, and renewal, and they confer many intangible aesthetic and cultural benefits as well".*

The range of ecosystem services provided by grassland biomes includes but not limited to meat, milk, wool leather, maintenance of atmospheric composition and hereditary library, amelioration of water and conservation of soils (Sala and Paruelo, 1997; Kang *et al*., 2007). As regards ground for social interactions, grasslands are areas of large diverse biodiversity which allows for human-environment interactions. This human-environment interaction allows for the (re)production of goods and services. One major source of attraction from the interaction is the abundance of genetic resources available for humankind within grassland biomes (Sala and Paruelo, 1997). As pointed out by Sala *et al*. (Sala and Paruelo, 1997 p. 264):

> *"Grasslands represent the natural ecosystem from where a large fraction of tame species originated, and where wild populations associated to the domesticated species and their linked pests and pathogens still thrive [social interactions]. These areas are most likely to offer new strains that are resistant to diseases or comprise of new features important for humankind".*

One of the important ecosystem services provided by grasslands is the maintenance of atmospheric composition in terms of carbon sequestration. Carbon sequestration is the process through which atmospheric CO_2 is secured in other long-lived carbon (C) pools to prevent them from being accumulated in the atmosphere (Lal, 2008). Sequestration of large quantities of C in grassland soils is very important as regards maintaining the dynamics of the atmospheric carbon cycle (Fan *et al*., 2008). Whether below or above-ground, the storage of carbon in grasslands is very significant for the development of viable tactics for mitigating climate change at this scale. Most grasslands are threatened globally due to various direct and indirect anthropogenic factors such as an increase in the human population, deforestation, over-grazing, fires, and invasive species to mention a few. These anthropogenic factors in light of changing climates are becoming amplified leading to the gradual or total destruction of global grassland communities (Kang *et al.*, 2007; Moncrieff *et al.*, 2015). These transformations release carbon stocks sequestered in grassland biomes globally leading to the global accumulation of atmospheric carbon (CO_2). Even though several studies have presented carbon loss from various grasslands across the world due to various anthropogenic practices and natural disasters, there is still a gap in accounting for global carbon sink or loss from grassland biomes, especially from the grasslands of the mountainous environments that are largely underrepresented (Ward *et a*l., 2014).

Mountainous grasslands, like other lowland grasslands, are facing threats but more importantly, the mountainous grassland soils face unique threats such as historical intensive use by humans, a greater amount of rainfall, snow cover, steep topography inhibiting extensive peatlands development, and natural turbulences like that of rockfall, soil destruction, spring snow defrost and slides (Ward *et al.*, 2014). Even though mountainous areas are largely inaccessible due to rugged terrains and harsh weather conditions, human activities around this area by the 'mountain people' and other people from nearby lowland areas imprint on this biome and damage this unique biodiversity which most often than not is irreversible (Ward *et al.*, 2014). Transformation of mountainous grasslands yields loss of carbon stock unfortunately, their distribution, extent and volume are still of growing concern as these areas are yet to be extensively studied and accounted for in global carbon emissions as against their lowland counterparts (Ward *et al.*, 2014). Understanding the carbon sequestration of mountainous grasslands requires a methodological design that can access remote areas with rugged terrains. Hence, this review aims to present approaches to studying biomass (above or below) in mountainous grasslands and their challenges using remote sensing technologies.

Biomass is allied with various essential components, such as soil nutrient provisions, carbon cycles, fuel increase, and habitat surroundings in terrestrial ecosystems (de Castilho *et al.*, 2006; Smith *et al.*, 2015; Lu, 2006; Sawadogo *et al.*, 2010). Plants are responsible for biomass production through the process of photosynthesis. When plants are burned or transformed, the stored energy, in this case, carbon dioxide, $CO_{2,}$ is released into the atmosphere. CO_2 is the utmost important greenhouse gases (GHGs) influencing global warming. Hence, biomass is very basic in understanding stocks of carbon in plant communities and most especially in mountain grassland environments (Fan et al, 2008). Even though field measurements stand as one of the most important ways to estimate biomass especially in lowland areas, the situation in mountain grasslands is different. The rugged terrain, altitudinal extent and remoteness of most mountain areas render intensive field measurement for biomass estimation to be a laborious. Therefore, the ability to measure and derive estimates of biomass remotely from observation platforms stands as one of the most unique ways to overcome this challenge. The ability to appropriately harness the utilities of remotely sensed products using remote sensing techniques will go a long way in ensuring improvement in biomass mapping in the light of the changing climates.

Remote sensing, in contrast with traditional approaches, offers spatial and temporal data that are convenient to mapping biomass at different spatial scales in a more vigorous, rapid and efficient manner (Fajji, 2015). Several studies have considered biomass estimation using Geographic Information Systems (GIS) and Remote Sensing (RS) practises (Fang *et al.*, 2001; Lu, 2006; de Castilho *et al.*, 2006; Ghasemi *et al.*, 2011; Attarchi & Gloaguen, 2014; Barbosa *et al.*, 2014; Dube et al., 2016; Baccini *et al.*, 2004; Chapungu *et al.*, 2020). Very few have considered biomass estimation on mountain vegetation (Attarchi & Gloaguen, 2014; Barrachina *et al.*, 2015; Brovkina *et al.*, 2017; Cho & Skidmore, 2009; Du *et al.*, 2020; Massetti & Gil, 2020; Sarker & Nichol, 2011; Soenen *et al.*, 2010; Sun *et al.*, 2002). However, studies on biomass estimation on mountainous grasslands using GIS and Remote Sensing are still growing especially in areas outside China, the ones available are largely field-based studies (Ward *et al.*, 2014) especially in Africa. Out of all these, only a few studies have considered below-ground biomass estimation for grasslands in mountain environments (Fan *et al.*, 2008; Gill *et al.*, 2002; Koala *et al.*, 2017). There is a necessity for contributions for biomass estimations in mountainous areas with improved studies focusing on below-ground biomass for mountain grasslands. This review is divided into the following sections: above-ground biomass and remote sensing, AGB and RS, below-ground biomass and remote sensing, BGB and RS, biomass estimation in mountainous grasslands of Africa; issues and challenges, and finally a conclusion.

2.2. Mountain grasslands

Mountainous grasslands are one of the most richiest place with diverse specie ecosystem. Its primary function is to provide food for domestic grazing animals. Mountainous grasslands are experience a drastic change due to evolution and human activities, that also leds to change in its landscape and species. Most mountainous grasslands occupy the largest area in the worldwide. According to Schermer *et al*., (2016), Switzerland mountainous grassland occupy about 940’000 ha, that is almodt one quarter of the total land area. Due to an increase in world’s population that triggers the human activities such as intensification of grasslands management, altered grazing, extensified land use of marginal grasslands, the mountainous grasslands are decreasing. Over the years grazing and land use capabilities have permanently shaped the mountainous grasslands together with the socio economic activities which also changesd the landscape of the mountain areas. Food production has been increasingly decoupled from the preservation of permanent grassland, endangering the delivery of crucial ecosystem services (Hinojosa et al., 2016).

2.3. Above Ground Biomass (AGB) and Remote Sensing (RS) in mountainous grasslands

There has been considerable progress in the use of optical sensors in forest studies especially in the appraisal of above-ground biomass (AGB) of grasslands. Visual remote sensing uses the detectable, near-infrared, visible and short-wave infrared sensors for creation of images across the surface of the earth by spotting the solar energy/emmision reflected from objects on the surface. In simple terms, it makes use of natural radiation from the sun and provides a two-dimensional view of grasslands and other earth surface topographies. Most optical images are freely accessible and affordable and have allowed a large number of studies to freely use the products from optical sensors. AGB estimation in lowland grasslands has proved successful using either active or passive optical sensors (Niu & Ni, 2003; Ali *et al*., 2017; Guerini Filho *et al*., 2020).

Data from multispectral sensor such as the Landsat MSS, TM, Advanced Very High-Resolution Radiometer (AVHRR) has been fruitfully used in many diverse areas across the world for estimating grassland biomass (Niu & Ni, 2003; Nguyen *et al*., 2020), while some others have enhanced grassland biomass estimation with machine learning algorithms (Adepoju & Adelabu, 2020; López-Serrano *et al*., 2019; Silveira *et al*., 2019), their use in montane grassland studies is largely constrained and remains limited (Barrachina *et al*., 2015;

Chapungu *et al.*, 2020; Sarker & Nichol, 2011: Jia *et al.*, 2016; Mohd Zaki & Abd Latif, 2017; Chu & Chu, 2020). These constraints are due to the regular cloud circumstances that frequently detain the acquisition of high-quality remotely sensed data by optical sensors (Mohd Zaki & Abd Latif, 2017; Xu *et al.*, 2020). Furthermore, vegetation indices (VI) computed from these optical sensors reaches a saturated-level on high-density for biomass estimation (Mutanga and Skidmore, 2004). In their study, on narrow-band vegetation indices, Mutanga and Skidmore (2004) posited that limited channels on multispectral images restrict the estimation of vegetal indices like the Normalized Difference Vegetation Index (NDVI) because they asymptotically approach a saturation level once a certain biomass density has been reached due to growing seasons, a view upheld by several authors (see, Mutanga and Skidmore, 2004).

Despite the limitations in multispectral products, there has been some success in literature using hyperspectral remote sensors such as Hyperion, Sentinel, Moderate Resolution Imaging Spectroradiometer (MODIS) (Cho & Skidmore, 2009; Li *et al.*, 2010; Zhang *et al.*, 2020a). The success level recorded through the use of hyperspectral remote sensors in montane grasslands is as a result of the usage of narrow-band vegetation indices worked out from hyperspectral data and high spectral resolutions to estimate biomass (Li *et al.*, 2010; Zhang et al., 2020). Especially with some results showing that modified vegetation indices calculated from the red-edge and near-infrared shoulder domains can estimate biomass with high accuracy (Mutanga and Skidmore 2004; Chen *et al.*, 2009) as associated to the average red or infrared-based indices. Huete *et al.*, (2002) and Timothy *et al.*, (2016) also concluded that hyperspectral products are operational at local to a global scale and that they provide globally consistent spatial data. Cho and Skidmore (2009) in their study conducted within the Majella National Park, Italy, a Mediterranean montane area, between 2004-2005, extracted VI, (narrow-band NDVI, modified soil adjusted vegetation index, NSAVI, and normalized difference water index, NDWI) and also red-edge positions (REP) from HyMap image, an airborne hyperspectral imaging sensor. They concluded in their study that VIs are a weak predictor of grass/herb biomass within the study area. However, they concluded that narrow-bands in the red-edge positions are more consistent predictors of biomass estimations in montane grasslands. The limitations as regards hyperspectral data source including but not limited to cost, availability, processing and high dimensionality.

Generally, whether it is hyperspectral or multispectral, Lu (2006) and Wu *et al* (2016) affirmed that the practice of coarse spatial resolution sensors such as Landsat, MODIS and

AVHRR, estimation of AGB especially in montane grassland results in poor forecast accuracy because of the occurrence of mixed pixels composed with a mismatch between the size of sections and the pixel since the area consists of different landscapes. Therefore, from the foregoing, the passive optical sensors are limited for effective estimation of biomass in montane grasslands. The available option is to seek solutions in the use of active sensors of light detection and ranging (LiDAR) and radio detection and ranging (RADAR).

The active microwave remote sensor, RADAR, is one of the ways of obtaining remotely sensed data in a given time framework regardless of weather or light circumstances. Due to this distinctive feature, RADAR data compared with optical sensor data, have been used broadly in many fields, also with forest-cover identification, mapping, discrimination and stratification. The extensive use of RADAR products is because of the longer wavelengths in unique bands (P, L, Ka, X, etc) in various polarizations (HH, VV, HV, VH) which ensures greater penetration of the medium or objects. The information on RADAR products is better enhanced based on the received backscatter from the object. The major constraint in the use of RADAR products is on the ability of the material to absorb microwave energy (dielectric properties). However, in grassland studies, these constraint is not a problem. Studies on grassland biomass estimation have shown the usefulness of RADAR data (Castel *et al.*, 2002; Kuplich *et al.*, 2000, 2005; Sun *et al.*, 2002; Sun et al., 2019), while others have shown their application in montane grasslands (Ghasemi et al., 2011; Sun *et al.*, 2002; Zhao *et al.*, 2020). Different RADAR data have their characteristics per vegetal constraints (Leckie *et al.*, 1998). For example, Radar backscatter in the P and L bands are highly correlated with major forest parameters, such as tree age, tree height, DBH, basal area, and AGB (Sun *et al.*, 2002). In particular, SAR (Synthetic Aperture Radar) L-band data (HH polarization) proves to be extremely valuable for biomass estimations (Table 2.1).

Another active sensor is the Airborne LiDAR (Light Detection and Ranging). LiDAR has demonstrated to hold great promise in biomass studies (Laurin *et al.*, 2012; Zolkos *et al.*, 2013; Brovkina *et al.*, 2017; Mohd Zaki & Abd Latif, 2017). LiDAR sensors are high resolution and active remote sensing tool that uses lasers to measure the distance between the sensor and an object. The sensor is capable of gaining accurate, high-resolution measurements of surface elevations (Bufton *et al.*, 1991). Some studies have shown the ability of LiDAR in grassland biomass estimations (Luo *et al.*, 2017; Marcinkowska-Ochtyra *et al.*, 2018; Radecka *et al.*, 2019). Furthermore, airborne LiDAR can offer information about the covering surface, volumes, biomass, and height of vegetation and a precise topography elevation classification (Popescu *et al*., 2003; Nelson *et al*., 2003: Naesset & Okland, 2002). This capability makes LiDAR ideal for montane grassland studies (Table 2.1). The only limiting factor here for LiDAR is in its acquisition. LiDAR images are expensive to acquire.

2.4. Below Ground Biomass (BGB) and Remote Sensing (RS) in mountainous grasslands

Below-Ground Biomass (BGB) is the biomass totality of living roots except for those roots smaller than 2mm in diameter. Live roots less than 2mm in diameter are largely excluded because of the yet-to-be verified difference between these roots and soil organic matter. Globally, BGB accounts for about 20% of the total biomass. Therefore, the direct estimation of below-ground biomass is very important especially in estimating total carbon pool and understanding carbon loss and storage for specific environments. The challenge however is in the estimation of BGB. Conventionally, the following methods are used in the estimation and monitoring of BGB. These are the quarry of roots, soil core or pit for non-tree vegetation, monolith for deep roots also root to shoot ratio and allometric equations (Fan *et al*., 2008; Peng *et al*., 2020; Yang *et al*., 2009). BGB estimations for most grassland studies have employed the above-listed methods or a combination of field-based studies.

Compared to AGB, BGB of grassland communities are still growing in the literature (Chapungu *et al*., 2020; Guerini Filho *et al*., 2020). BGB studies of grassland communities of mountanious environments are very rare with most present studies concentrated within the Tibetan Plateau (Peng *et al*., 2020; Shi-Long *et al*., 2004) or greater China. The use of remote sensing techniques in the estimation of BGB is still growing even for lowland studies. Chapungu *et al*. (2020) estimated BGB of savanna grasslands using an indirect relationship between AGB and BGB and then comparing that with NDVI. In their study, they stated the limitations of multispectral data especially those obtained from Landsat images. They concluded that for grassland biomass estimation, the more recent multispectral sensors of Sentinel–2 and Worldview-3 holds great promise (Chapungu *et al*., 2020) especially for BGB estimations in the red-edge region. There is still a need for more studies on BGB estimations for mountainous grasslands using remote sensing techniques to fully understand these unique ecosystems and their dynamics (Table 2.1).

Worldview-2 is a newly invented generation satellite with a moderate resolution that is coupled with or trade-off benefits of both multispectral resolution satellite data and hyperspectral data. It is unique such a sensor that has a rational number of spectral bands that are arranged in unique rations of the electromagnetic spectrum and comprises the red edge.

Worldview-2 gives extra wavebands (8 bands) and greater spatial resolution (2m) than other traditional broad bands satellite images such as SPOT and Landsat TM while decreasing excessive redundancy as enclosed in hyperspectral (Sridharan, 2010). Imageries such as Worldview-2 & 3 and Rapid Eye (Gascón *et al*., 2019) incorporate the red-edge bands which have been identified as key bands for predicting and mapping grassland ecosystems (Ramoelo *et al*., 2012; Ramoelo *et al*., 2015; Sibanda *et al*., 2017; Huang *et al*., 2017). The European Space Agency (ESA) launched a new generation high spectral resolution sensor named Sentinel-2 MSI around June 2015. Sentinel-2 has a spectral band similar to those of Worldview-2 and RapidEye. Sentinel-2 is a multispectral instrument with 13 spectral channels with an actual big swath (290 km) with a high return to frequency of about 5 days periodicity at the equator and systematic procurement of all land surfaces and coastal waters (Luther, 2006; Sibanda, 2017). The qualities of Worldview-2 and 3 and Sentinel-2 offer great hope into biomass estimations of grasslands even those of the mountain areas.

Synthetic Aperture Radars (SARs) are dynamic sensors functioning within the microwave regions (Bergen & Dobson, 1999). SARs sense more of the standing forests than other optical sensors. Hence they yield better estimates for BGB. Bergen and Dobson, (1999), integrated SAR datasets into the estimation of Net Primary Productivity (NPP). They posited that the derived SAR datasets from the SIR-C satellite sensor provide good estimates of below-ground biomass (Table 2.1). LiDAR also holds great promise for forest inventory, especially BGB (Næsset & Gobakken, 2008). Næsset *et al*. (2008) in their study on boreal forests concluded that Airborne LiDAR Systems (ALS) holds great promise in below-ground biomass estimations with good accuracy. In another study conducted in the middle Heihe River Basin, northwest China (Luo *et al*., 2017) it was concluded that the fusion of LiDAR data with hyperspectral products provided a better accuracy for BGB by yielding the lowest root mean square error (RMSE) when compared with BGB estimates from the LiDAR data alone.

Summarily, for biomass estimations (above or below) the use of active sensors holds great promise and opens a world of opportunities. LiDAR has immense capabilities to offer in the estimation of biomass especially in mountainous environments. Even though studies using remotely sensed products to estimate below-ground biomass of mountainous grasslands are very few globally, the inherent characteristics of these active sensors and their applications in lowland areas show that their application in mountanious areas cannot be overemphasized. RADAR images have longer wavelengths hence, they can penetrate further than optical sensors and coupled with the fact that RADAR images are low-cost and some are even freely available makes it even better for mountainous environments in Africa. The technical detail and especially the cost of acquisition of LiDAR are enormous, especially for researchers, students and academics in Africa. The emergence of Sentinel satellite missions provides unlimited RADAR products for some selected bands at no cost. Also, Worldview – 2 and 3, RapidEye satellite missions provide datasets with multispectral channels that can be fused with RADAR images to improve the quality of biomass estimations across mountainous environments. This in essence provides a way out to improve studies on mountainous biomass grassland estimations across the world and especially in Africa (Table 2.1).

Table 2.1. Biomass estimation: sensors, findings and references from 1997 - 2020

SENSOR (S)	ELEVATION	FINDINGS	REFERENCES
OPTICAL SENSORS			
Landsat TM, 8 OLI,	Lowland	Landsat archive is a great resource for reconstructing grassland areas and Landsat 8 OLI improves the estimation of AGB using SVM as against traditional regression models.	(Dara *et al*., 2020; Deb *et al*., 2020; Dube & Mutanga, 2015)
Landsat-5	Mountain	As against known VI such as NDVI, the study used wetness indices and concluded that middle infrared bands are fundamental descriptors of AGB in mountain areas of Pyrenees.	(Barrachina *et al*., 2015)
MODIS	Lowland/Mountain	The capability of MODIS with or without climatic variables and VI provides good estimate of AGB across lowlands or mountain environments.	(Ali *et al*., 2017; Baccini *et al*., 2004; de Leeuw *et al*., 2019; Dingaan & Tsubo, 2019b; Du *et al*., 2020)
RapidEye	Lowland	RapidEye is identified as a suitbale product for biomass estimation because of its spectral information in the red-edge channel that is optimal to detect and describe vegetated classes.	(Gascón *et al*., 2019; Massetti & Gil, 2020)
Sentinel-2	Lowland	Biomass estimation was satisfactory even in the red-edge band.	(Guerini Filho *et al*., 2020b)
Sentinel-2, HyspIRI	Lowland	The study posited that low-cost and readily accessible multispectral data such as the Sentinel-2 has great prospects for large-scale biomass monitoring.	(Sibanda *et al*., 2016)

Systéme Pour lObservation de la Terre (SPOT)-VGT[a], SPOT-5[b]	Mountain	[a]It was established that the (SPOT) NDVI-biomass relationship can be quantified exponentially. [b]The ability to derives forest structure from SPOT-5 imagery when coupled with a physically-based canopy reflectance (CR) model inversion approach such as the multiple forward mode (MFM) provides a better estimate for biomass in mountainous environments.	(Liu *et al.*, 2015[a]; Soenen *et al.*, 2010[b])
HyMap	Mountain	The red-edge position computed from a Lagrangian interpolation and linear extrapolation produced a lower predictive error for biomass estimations as compared to NDVI.	(Cho & Skidmore, 2009)
Landsat 8	Mountain	The established spectral model (ground measurement with remote sensing inversion) provides technical support for high-precision large-area productivity valuation and ecological degradation verdict of regional-scale grassland.	(Zhang *et al.*, 2020b)
ZY-3	Mountain	The results showed that integration of Relative Canopy Height-based variables and spectral data significantly improved AGB estimation performance when compared with the use of spectral data alone. This goes a long way in solving the issue of data saturation in optical sensors.	(G. Li *et al.*, 2019)
ACTIVE OPTICAL SENSOR			
LiDAR	Lowland	The capability of LiDAR instruments in measuring the vertical structure of forests including canopy height and fractional cover holds great promise for remotely sensing the quantity and spatial organization of forest biomass. These studies show the relationships between these structures	(Knapp *et al.*, 2020; Lefsky *et al.*, 2002; Dongliang Wang *et al.*, 2017)

		and grassland biomass.	
	Mountain		(Jiang *et al*., 2020; Y. Wang *et al*., 2019)
MICROWAVE			
SIR-C	Mountain	The image tone (backscatter) potentially rises the precision with which SAR data can be used to estimate biomass either above or below-ground across various elevations.	(Bergen & Dobson, 1999; G Sun *et al*., 2002)
JERS-1/SAR	Lowland		(Kuplich *et al*., 2005; Kuplich, Salvatori, *et al*., 2000)
AIRSAR	Lowland		(Ranson *et al*., 1997)
L-band Soil Moisture and Ocean Salinity satellite (SMOS)	Lowland	Better estimates of AGB are obtained by the joint use of vegetation optical depth (VOD) derived from L-band SMOS and some climate variables.	(Vittucci *et al*., 2019)
L-band Advanced Land Observing Satellite (ALOS) Phased Array L-band Synthetic Aperture Radar (PALSAR)	Lowland	These studies posited that the use of ALOS/PALSAR backscatter reduces the uncertainty in the estimation of AGB in the tropics.	(Carreiras *et al*., 2012; Mitchard *et al*., 2009)
RADAR AND LiDAR FUSION			
SAR + LiDAR	Lowland/Mountain	Although the results are still far from being conclusive, these studies show the possibility in the combination of LiDAR and SAR data for biomass mapping (above or below-ground) across various locations.	(Guoqing Sun *et al*., 2011; Ni *et al*., 2019)
OPTICAL AND RADAR SENSOR FUSION			
Sentinel 1 and 2	Lowland	Backscatter, spectral reflectance, and derivatives (vegetation indices and biophysical parameters) were combined in a Random Forest regression to map AGB. The study posited that incorporating Sentinel 1A and Sentinel 2A reflectance bands, in particular, yielded higher accuracies of AGB.	(Forkuor *et al*., 2020; Naidoo *et al*., 2019a)
	Mountain		(Nuthammachot *et al*., 2020)
ALOS/PALSAR with	Mountain	Landsat TM data perform	(P. Zhao *et al*., 2016)

Landsat TM		better than PALSAR data, but the latter can produce more accurate estimates for bamboo and shrub, and forests. However, the combination of TM and PALSAR data as extra bands can greatly improve AGB estimation performance but not without a caveat in their fusion using the modified high-pass filter resolution-merging technique.	
ALOS/PALSAR with Landsat ETM+	Mountain	Adding SAR backscattering as well as PolSAR features and textures to the use of revised ETM+ spectral bands and GLCM textures improves the accuracy of AGB estimation meaningfully. They posited that these fusions are vital for the estimation of mountain forest's physical properties.	(Attarchi & Gloaguen, 2014)
LiDAR AND OTHER OPTICAL SENSORS FUSION			
LiDAR and hyperspectral	Lowland	The result from these studies demonstrated that biomass accuracies could be improved by the use of fused LiDAR with either hyperspectral or multispectral data as compared to the use of LiDAR data alone. In conclusion, fusion of LiDAR and other remotely sensed data has great potential for improving biomass estimation accuracy across different elevations.	Composite Airborne Spectrographic Imager (CASI) - (Luo *et al.*, 2017) AISA Eagle Sensor - (Vaglio Laurin *et al.*, 2014a)
LiDAR and multispectral	Lowlands		Pleiadas image - (Rapinel *et al.*, 2018) IKONOS – (St-Onge *et al., 2008)*
	Mountain		Landsat TM/ETM+ - (Dong *et al.*, 2019) Sentinel 2 - (Dezhi Wang *et al.*, 2020)

2.5. Biomass estimation in mountainous grasslands of Africa: issues and challenges

The issues and challenges surrounding African grasslands can be conceptually captured using the DPSIR (Drivers, Pressures, State, Impact, and Response) Framework (Agyemang *et al.*, 2007). However, before delving into the challenges and issues, a background into existing studies will be provided. Few studies have been carried out on the estimation of grassland biomass in African environment using remote sensing techniques (Fajji, 2015; Shoko *et al.*, 2016; Sibanda *et al.*, 2016; Timothy *et al.*, 2016; de Leeuw *et al.*, 2019; Dingaan & Tsubo, 2019; Naidoo *et al.*, 2019). Most studies have focussed on the estimation of different woodland biomass within the African environment than on mountainous grasslands (Baccini et al., 2004, 2008; Balima et *al.*, 2020; Carreiras et al., 2012, 2013; Chapungu *et al.*, 2020a; Day *et al.*, 2014; Forkuor *et al.*, 2020; Gascón et al., 2019; Knapp et al., 2020; Mitchard *et al.*, 2009; Sainge *et al.*, 2020; Timothy *et al.*, 2016; Vaglio Laurin *et al.*, 2014b; Vittucci *et al.*, 2019). However, general studies on grasslands in mountainous environments are common (Adagbasa *et al.*, 2020; Adagbasa, Adelabu, & Okello, 2019a; Adepoju & Adelabu, 2019) but biomass studies are very few and far in-between if any. Most of the studies monitoring, mapping and estimating biomass have been carried out within the greater forested environment using remote sensing and GIS coupled with conventional (traditional methods). Furthermore, literature gathered from key peer-reviewed remote sensing journals revealed staggering information on biomass studies within Sub-Saharan Africa, (SSA) (Figure 2.1). Almost all the studies if not all carried out within Africa focused mainly on AGB with little or nothing focusing on BGB especially within SSA between 2002 – 2019 (Figure 2.2).

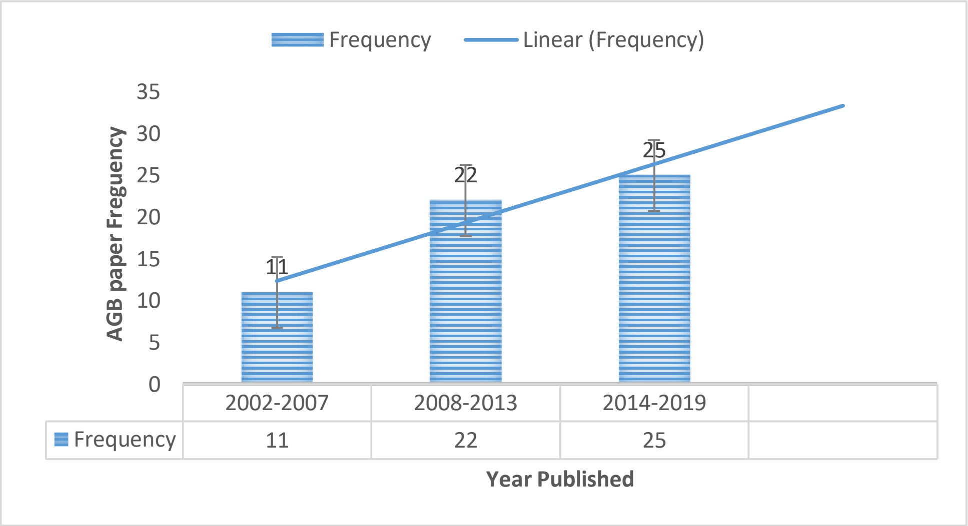


Figure 2.1. Growth of remote sensing popularity in AGB mapping in sub-Saharan Africa between 2002 and 2019

Fifty-eight (58) articles were reviewed and amongst them only three of those papers were on mountain terrain. Fifteen (15) of those papers were on grasslands and the rest were on forest using remote sensing and GIS techniques (Figure 2.1). This shows that works on grasslands in Africa and its mountain areas are far lesser than those on the Americas and China. The ones concerning Africa are predominantly within the SSA (Figure 2.2). Most of the studies on grassland communities in Sub-Saharan Africa have employed various sensors such as the optics and microwave (Figure 2.2). This shows that the basic requirement and datasets required for grassland studies are available but reasons for the low turnout on mountain grasslands remain yet unsolved.

The grasslands of Africa are savanna, asides the velds of Southern Africa. The savanna in Africa is the most extensive in the world covering almost half of the continent. Grasslands of Africa (savanna and the velds) forms a significant component of Africa's terrestrial ecosystem covering not fewer than 30% of the terrestrial area and contributes about 20% of the entire terrestrial primary productivity. In Africa especially in the southern part of the continent, grasslands are said to be an entirely important source of livestock forage, which do support the entire livelihood of the community depending and relying on it as well as the wildlife population (Schmidt and Skidmore, 2001; Xu and Guo, 2015).

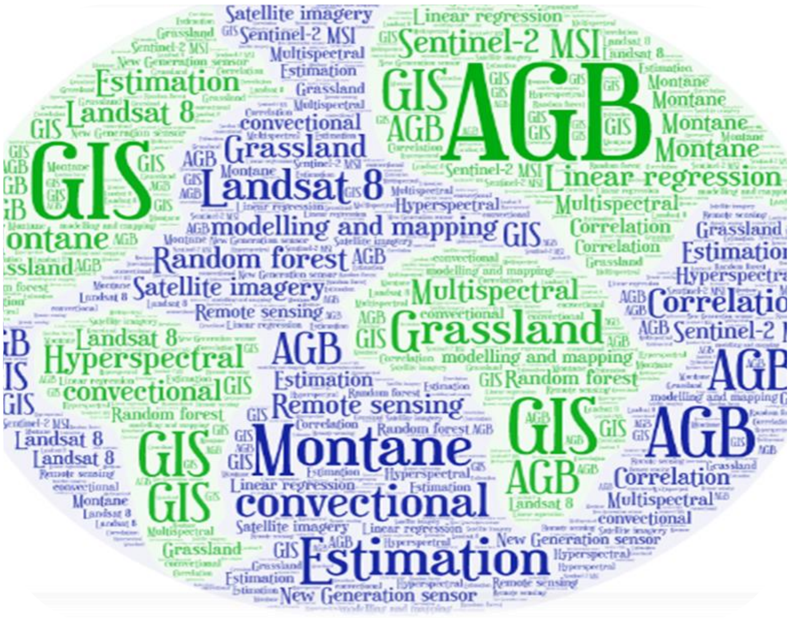


Figure 2.2. A portrait of Africa and sensors used in grassland biomass estimation

As with other biomes of the world, the *drivers* of African grasslands (Figure 2.3) are largely human populations, livelihood patterns, wildlife and landuse/landcover. These drivers put a strain on the grassland communities and ecosystem provisioning. These drivers create pressure on the grassland community through various human activities such as: fires, urbanization, cultivation, climate change, grazing, and invasive species. (Balima *et al*., 2020; Brink *et al*., 2014; Gallego-Zamorano *et al*., 2020; Harrison & Shackleton, 1999; Newbold *et al*., 2017; Waters *et al*., 2019) and for that, alters the *state* of the grassland biome completely. The *state* of the African grassland community at present is an accumulation of pressures over the years. Across the continent, the grassland community in some quarters have witnessed gradual destruction while some have been completely wiped out. The gradual change or changes being witnessed across African grassland environments is a major contributor to total carbon loss into the atmosphere (Chapungu *et al*., 2020). The practice of satellite records has proved useful in the understanding of pressures and state. It has remained helpful in detecting patterns of both interannual and seasonal variations of the land surface features as a result of various pressures such as fires (Adagbasa, Adelabu, Okello, *et al*., 2019; Adelabu *et al*., 2018; Adepoju & Adelabu, 2019), anthropogenic activities (direct and indirect) (Adagbasa, Adelabu, & Okello, 2019b; Adagbasa, Adelabu, Okello, *et al*., 2019; Adeola Fashae *et al*., 2020) and consequences of climate change (Propastin *et al*, 2006) such as drought, dehydration, instabilities in rainfall patterns (Balas *et al*., 2007), and high temperature (Xiao & Moody, 2004). These climatic variables and other pressures including anthropogenic are products that are fully captured from remotely sensed platforms at various resolutions and are disseminated daily, hourly, seasonally and monthly, based on the observing satellites, sensors, their orbits and objectives (Wang *et al*., 2003).These techniques can be applied over Africa with a more focused and concerted effort. The *impact* of these increases the total amount of greenhouse gases (GHGs) being released into the atmosphere. There is therefore a need to respond by arresting the threat to grassland communities not only to save the community but also to preserve the entire environment and forestall the increasing impact of climate change. The response of governments and stakeholders such as: conservationists, park rangers, environmentalists, academia, the communities, is to work together and be involved in the co-production of knowledge and sustainable methods that would help save the grasslands of Africa (Figure 2.3). Therefore, adequate and enhanced environmental monitoring using remotely sensed products and techniques (Table 2.1) proves to be a reliable means of monitoring the impact, variations and dynamics of the changing African grassland communities especially the mountain grasslands of Africa (Booth & Tueller, 2003).

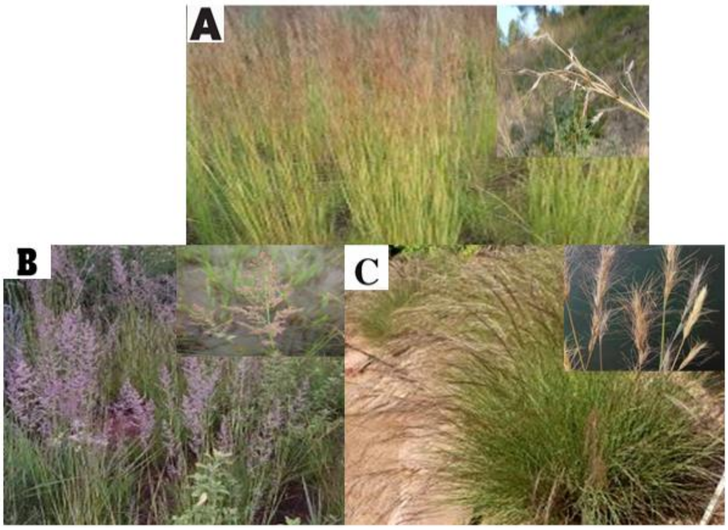


Figure 2.3. Some grass species in Africa with drought-resilient capabilities
A - *Hyparrhenia hirta*; **B** - *Eragrotis Gummiflua* and **C** - *Aristida Congesta*

Therefore, one major way out is the effective use of remote sensing techniques and geographic information systems, in a more coordinated manner which includes but not limited to the establishment of mountain research units in various zones of the continents such as the Afromontane Unit in South Africa, to focus on mountain activities across these zones in Africa. Together, these units using remotely sensed products and ground-based datasets to monitor map and understand more closely the mountainous grassland biome will eventually help in the conservation and monitoring of grasslands in Africa and contribute to the global atmospheric storage of carbon. This will go a long way in the conservation and protection of biodiversity within the grassland biomes in Africa. The stability and the resilience of the ecosystem largely depend on this to ensure the continued supply of ecosystem services from this threatened biome, in quality and quantity as and when needed.

2.6. Conclusion

The climate within mountain areas is normally sub-tropical with marked altitudinal slopes of air humidity and temperature, rainfall,wind conditions and cloudiness. Mountain regions are covered by the variability of vegetation types of large exclusive to their environments and some of these grasses are yet to be fully classified and identified especially in Africa. Herbaceous mountain areas are largely inaccessible due to obvious reasons (e.g. elevation) which make it difficult to overcome. However, remote sensing platforms offer a solution since it is a technology that gives facts of a very high resolutions and is also independent on the topographic conditions.

Optical sensors with very high spatial resolutions and with either wider or special spectral bands such as Sentinel-2, RapidEye and Worldview have great potential in biomass estimation. These optical satellites when fused with either RADAR or LiDAR provide enhanced information on biomass estimations in mountainous regions especially in the red-edge positions. Other positions along the electromagnetic spectrum like that of the red and near-infrared are also of importance but a more restricted and sensitive to weather conditions making satellites such as the NOAA, AVHRR, MODIS and Landsat not too strong at these elevations. They (NOAA, AVHRR, MODIS, and Landsat) are coarse, weather-biased and in terms of optics and scale they are of extremely limited capacity in biomass estimations in mountain environments especially the below-ground biomass estimations.

The best alternative is the RADAR or LiDAR, which offers an exceptionally high-resolution image with 3D data and it is suitable for a very extensive variety of applications, including biomass estimations. The way forward as regards mountain biomass estimations therefore, lie in the use of RADAR and LiDAR products but for more enhanced estimations and accuracy the fusion of these (RADAR and LiDAR) with multispectral images such as RapidEye, Worldviews and Sentinel-2. With this fusion there is great hope that in few years there will be an increase in studies on biomass estimation of mountanious grasslands globally and especially the below-ground biomass estimates in African mountain environments.

Chapter 3

This chapter is based on:

Mathapelo Semela, Abel Ramoelo, **Samuel Adelabu** *Testing And Comparing The Applicability Of Sentinel-2 And Landsat 8 Reflectance Data In Estimating Mountainous Herbaceous Biomass Before And After Fire Using Random Forest Modelling* ***Accepted*** IEEE Xplore IGARSS 2020

Abstract

Herbaceous biomass is an important indicator of rangeland quantity. Grasslands cover vast areas in South Africa. They supports livestock production which is crucial for livelihoods, biodiversity conservation and tourism. Grasslands, especially the mountainous ones, are threatened by several factors including global environmental changes. Others includes; overgrazing, the proliferation of invasive species and unmanaged fires. There is need to continuously monitor grasslands using geospatial technology. The objective of this study section was to test and compare the applicability of Landsat 8 and Sentinel-2 data acquired before and after fire events in estimating biomass using random forest. Models in both Sentinel-2 and Landsat 8 explicated over 80% with biomass differently in the mountainous areas. However, Sentinel-2 MSI model marginally perfomed better than Landsat-8 OLI model. Results indicate that Sentinel 2 and Landsat 8 together provide useful information on grass biomass estimation and assessments in mountainous environments.

Keywords*: Biomass, fire, random forest, Landsat 8, Sentinel 2, motuntain areas*

3.1. Introduction

Herbaceous biomass is the rangeland's focal instrument, essential to determine the quantity and amount of food accessible for grazers, comprising livestock and wildlife. Farley, (2007), denotes that "in recent times, much research has begun to characterize the functions or value of particular ecosystem services: such as carbon sequestration, pollination; with some explicitly recognizing how those functions change when land is converted to different uses". Livestock production in the rural areas of the world, Africa not excluded, is the main source of income which explains the kind of life style in a particular African continent. Grassland is full of rangeland which is a broad capacity of land that is engaged by natural herbaceous or shrubby vegetation, which is grazed by domestic or wild herbivores (Young and Evans, 1978, Landsberg *et al.*, 2003, Cingolani *et al.,* 2005). Rangeland magnitude impacts the feeding arrays and schedules of grazers (Bailey *et al.*,2018, Fust *et al.*, 2018 and Cau Diogo *et al.*, 2020). The availability and quality of grazing resources are now threatened by the myriad of bglobal environmental changes, including climate and land-use change, together with the proliferation of the invasive species. Therefore, there is a need to continuously monitor biomass, especially in the mountainous regions. The mountainous environments are characterized by rugged terrain which often challenges conventional field data collection. The use of remote sensing is ideal, as it covers a wider geographical area and repeatable.

For approximately four decades, remote sensing successfully estimated herbaceous biomass in many natural and farming areas, that has given it recognition in the current days (Tucker and Sellers, 1986; Xu, *et al.*, 2014; Naidoo *et al.*, 2019). The most used technique in biomass estimation is the vegetation indices (normalized difference vegetation index (NDVI)) that measures the vegetation greenness (Rouse *et al.*, 1974, Todd *et al.*, 1998).

Biomass estimation using NDVI has been achieved successfully using empirical models (Naidoo et al 2019, Schino *et al*, 2003, Shoko *et al.*, 2016). Empirical models are the easiest and simple to implement through location, period and data precise. They are also models for biomass prediction through the means of vegetation indices that has been effective in wet times when plants are green and photosynthetic vigorous (Mutanga, *et al.*, 2012, Ramoelo *et al.*, 2015). In a study carried out within a wetland area (Mutanga *et al.*, 2012), data from WorldView-2 and random forest and plantation algorithm were used to lessen the capacity difficult in assessing biomass in peak yield. Also, Ramoelo *et al.*, (2015), successfully assessed biomass using remote sensing products (i.e. reflectance and indices) and random forest to lessen the capacity problem during peak productivity or wet season applying WorldView-2. During peak productivity, the saturation problem occurs when the amount of light that can be absorbed in the red region of the spectrum reaches a highest peak (Tucker, 1977), whereas the NIR reflectance continues to surge due to the addition of new foliage that impacts the various scattering the canopy's center (Kumar *et al.*, 2001). In another study by Dube and Mutanga, (2015), it was posited that the multispectral Landsat 8 OLI imagery created probable above-ground assessments than the long-serving Landsat ETM+. In this study, the conclusion was that the Landsat OLI dataset provides better AGB estimation when using extracted spectral data with the consequent spectral vegetation indices. Thus, there are high accuracies of RMSE, Bias % from Landsat 8 OLI than that of Landsat ETM+ dataset. In studying the vigour of new Landsat 8 OLI (Dube and Mutanga, 2015), their results validated that all texture parameters particularly band texture ratio considered in a window size of 3x3 using Landsat 8 OLI could enhance AGB estimation as compared to simple spectral reflectance, simple band ratio and the general spectral vegetation indices.

Chrysafis *et al*, (2017) noted that Sentinel-2 bands except the blue and red parts of the spectrum given negative but major correlation resulted in mounting stock volume. Sentinel -2 MSI was found to be somewhat higher than Landsat-8 OLI. Again on Sentinel-2 MSI, bands and indices better projected aboveground biomass better than Landsat8 OLI bands and indices but there were no significant differences between the two in terms errors of predictions across all fertilizer treatments. Sentinel-2 is only good for regional-scale biomass estimation mainly in arrears which resources are scarce. (Sibanda *et al.*, 2015).

The strategic insertion of the red edge band in the satellite sensors was a solution to the issue of saturation. At the hyperspectral level, (Mutanga and Skidmore, 2004) and (Cho *et al.* 2007) demonstrated the applicability of the red-edge band in the estimation of biomass. On the other hand, there is a new sensor called Landsat 8, developed and forms the legacy of Landsat with high radiometric resolution as compared to its predecessors. In this study, we intend to test both Sentinel-2 and Landsat 8 images in the estimation of biomass using before and after fire images in the mountain grasslands that are often managed by controlled fire to improve the availability and quality thereof.

3.2. Materials and methods

3.2.1. Study research approach

Study followed a quantitative research approach methods that combined both field, ancillary and Remote sensing data (Figure 3.1). Quantitative methods usually starts with a specific theory about a particular subject which then leads to a aspecific hypothesis that are then measured qualitatively and rigorously analyzed to develop mathematical model (Holton and Burnett, 2005).

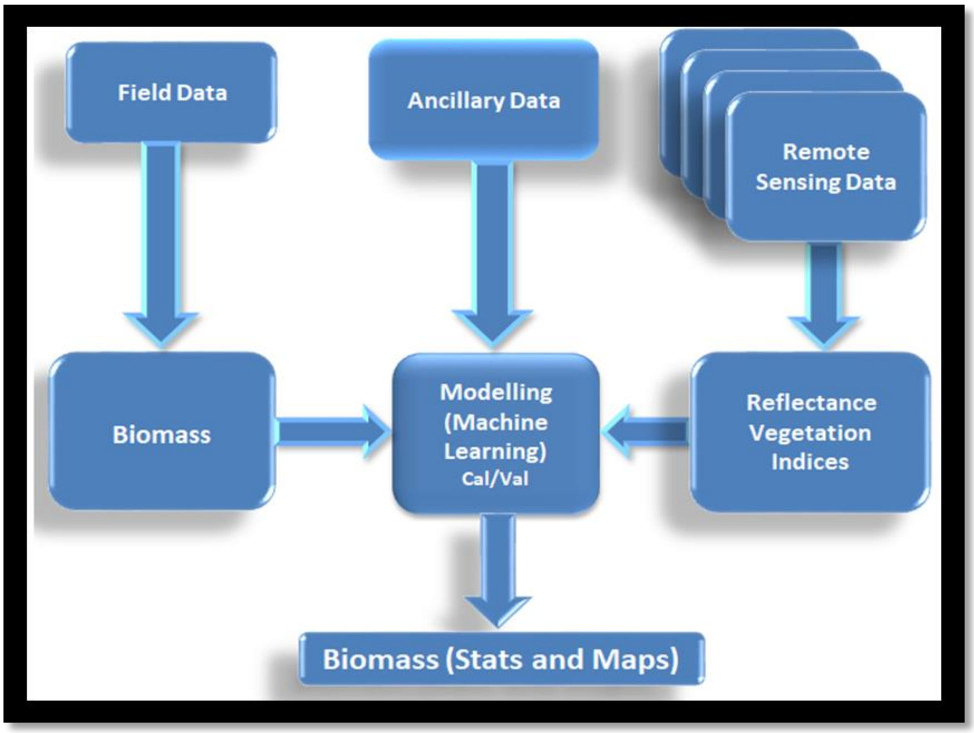


Figure 3.1. The research approach of above ground fresh grass biomass estimation using multispectral remote sensing

3.2.2. Study area

The study was conducted in the Golden Gate Highlands National Park (GGHNP), South Africa (Figure. 3.2). GGHNP has an estimated area of 32,758.35 ha and with the Caledon River in the southern margin and the edge between the Free State and Lesotho in the east. The area is situated between 28° 28' and 28° 37' S latitude and altitude 28° 33'and 28° 40' E longitude and also between 1 837 m and 3 099 m (Strydom and Savage, 2016).

Rainfall is around 800 mm per annum mainly in the summer (October–April) and thick Snowfall in relatively dry winter May–September (Adagbasa. *et al*, 2018). Annual precipitation fluctuates extensively throughout the area and it approximately is around ≥760 mm, mostly experienced between November to April (Mofokeng. *et al*, 2019). Summers are slightly warm with the mean temperature ranging between 13 °C to 26 °C and winters very cold since their mean temperature are between 1 °C to 15 °C in winter, (Cooks and Pretorius, 1987). There is a wide spread of Frost during the winter months with the seldom falls of snow on the higher mountains in the park (Groenewald, 1989). The geology of the area consists of

Molteno formation which is moderate to coarse-grained through cross-bedded sandstone, but Elliot creation contains of a thick series of red mudstone, siltstone and interlayered fine to medium grained, light yellow-brown sandstone (Groenewald, 1989).

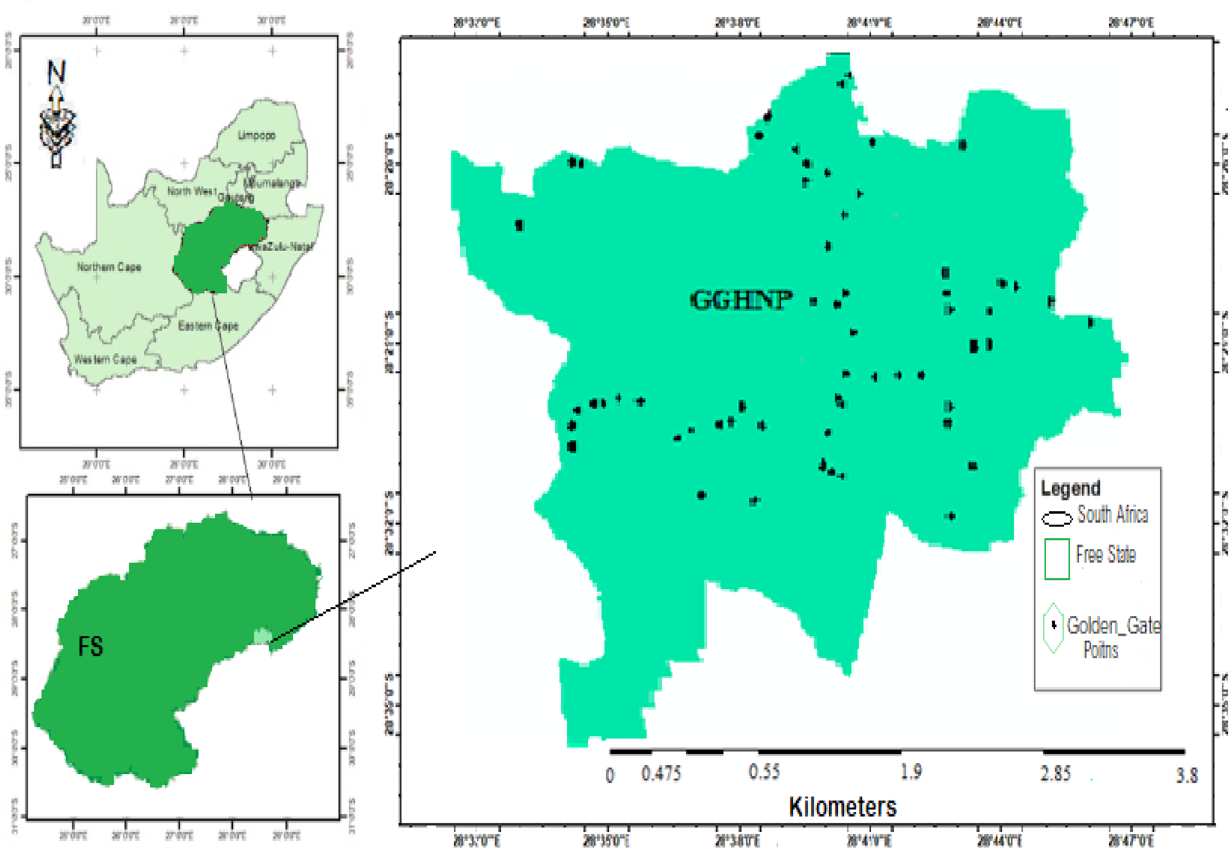


Figure 3.2. Study Area (GGHN Park) in the Eastern Free State, South Africa

The GGNHP is characterized by diverse and five dominant grass vegetation types such as Basotho montane shrublands; Drakensberg-Amatole Afromontane fynbos; Eastern Free State sandy grassland; Northern Drakensberg highlands grassland and Lesotho highland basalt (Mucina, and Rutherford, 2006). This park comprises of over 60 types of grass (Table 3.2) for few examples of these species. Since the park is a montane region, the high rainfall causes the soil to becomes acidic and this leads to what is named“sourveld” grassland (O’connor 2005, Adepoju and Adelabu, 2018). Usually, most grasses change to reddish color because of the red grass in summer seasons. (*Themenda traindra*) that breeds at the park (Wessels and Budel, 1995). This red grass indicates the grassland conditions and its grazing are exceptionally healthy and in good conditions, it is also one of the rare types of grass exterior to the park barriers were most of cultivation and overgrazing are mostly problematic.

Most of the grass species and other flora needs burning so that it can stay healthy through getting rid of the accumulated dead materials. Some parts may be left unburned to provide food for the animals through grazing, hence the fire breaks must be properly controlled to systematically spread the fire around the area. Fire in Golden Gate Highlands National Park is triggered primarily by humans either in a intended (management fires, arson fires) or accidental (runaway planned fires) manner. Fires from lightning strikes also occur as a form of natural fire phenomenon which cause the flora and fauna in the area to adapt to the fire regime. However, lightning is generally contained and infrequent. The management of the fire requires a significant financial and long term human investment to maintain the park.

Table 3.1*:* Different types of grass species found in Golden Gate Highlands National Park with their common names and descriptions. Sourced from: website **https://www.sanparks,org** (dated; 14 May 2020 at 19:54**)**

Scientific name	**Commonly known**	**Description**
Hyparrhenia hirta	Mostly used as a thatch grass, Dekgras, Legokwana in sesotho	A mostly found along the roadside areas especially the sunny slopes. It is 30-80 cm long and is a tufted perennial. It is extensively spread across the southern Africa. Significantly used as a source of grazing during spring season just before the leaves gets too hard. As a source of economical use, it is mostly used for roofing and to make a grain basket that stores grain up to 1.5 m across.
Themeda triandra	Red grass, Rooigras, Seboku in Sesotho	A 30-150cm tall flexible tufted perennial. One of the most vital sources of grazing in spring and summer. If it is mostly found or notable in a particular veld, the veld is considered as healthier as ever. It is not really a source of thatching and soft basket material but can be used as one when needs be.
Heteropogon contortus	Spear grass, Assegaaigras, Seloka in Sesotho.	It is mostly found in the lower areas and growing in clumps. It is up to 70cm long tufted perennial that is extensively spread in the Southern Africa. This grass has a sharp, thorn like ends that spikes when walking across it with shorts. this grass are mostly used as a medicine by the Basotho to heal the Rheumatism of the hands
Eragrostis chloromelas	Curly leaf, Krullblaar, Moseeka in Sesotho.	It is mostly found in the lower lying areas and it is 40-80cm tufted perennial. It is vital for socio economic uses such as food since during severe famine Basotho's' use its seedling to make brewed beer and bread. It is very tough grass that can withstand substantial grazing.
Merxmuellera drankensbergensis	Broom grass, Besemgras, Mohlabapere in Sesotho.	This grass is named after both German Botanist H. Merxmuller and the Drakensberg Mountains. It is a thickly tufted perennial, to 1m tall. Its very hard, springy leaves are not grazed at all. The leaves are found in the mop area on top of the mountains and escarpments, but only in deeper soil pouches in and around Lesotho and also Mpumalanga. It is the most hunted grass specie for hand-made products such as hats, brooms and baskets. Its fine folded leaves are also best in weaving the ropes to bind hats and baskets.

3.3. Data acquisition and pre-processing

3.3.1. Field Data collection

Hawth's analysis tool was executed to produce 60 random plots using the land coverage map of the study area. The 20x20m plots were then uploaded into Geo XT handheld GPS receiver. Within each plot, five 1m x 1m sub-plots were sampled (Ray and Murray, 1996) for harvesting grass biomass. The grass samples were cut at the ground level where fresh grasses were stored into the plastic bag while the dry and other leaves were removed. Thereafter, immediately the grass from each plot was put inside the envelop and evaluated to achieve a wet weight (g) of the grass.

The collected materials were transported to the research laboratory where the testers were dried up in the oven at 75°C for 72 hours and weighed once more to quantify the water content and total dry biomass, hereafter then referred to y6 as grass biomass (on the excel sheet). This was done for both pre and post-fire measurements. Pre-fire was taken in April while post-fire was taken in October 2018. Fire often occurs for the period of the dry season and is used for the management of the landscape.

3.3.2. Remote Sensing Data Acquisition and Pre-Processing

Both Sentinel-2 MSI and Landsat 8 imagery covering the study zone was obtained in April and October 2018 from the USGS Earth Resource Observation and Science (EROS) center archive (http://earthexplorer.usgs.gov/) to coincides with the pre and post-fire field data collection respectively. Sentinel-2 MSI mission comprises twin polar-orbiting satellites in the same orbit, phased at 180 to each other. The mission monitors variability in land surface condions and its wide swath width and high revisit time (10 days from the equator with one satellite, and 5 days with two satellites under cloud-free conditions which results in 2-3 days at mid latitude to support monitoring of changes to vegetation withing its growing season) with the coverage limits of from between latitude 56 south and 84 north (Radioux *et al.*, 2016). It comprises of 13 spectral bands with spatial resolutions extending from 10, 20 and 60 metres whilst Landsat-8 OLI consists of 11 spectral bands with spatial resolution extending from 15, 30 and 100 metres. Table 3.2 shows details of the two new-generation sensors data Landsat 8 OLI and Sentinel-2 MSI satellites. The metadata such as the site description (coordinates, altitude and land cover class) and general weather conditions were also recorded alongside the spectral measurements (Manakos et al., 2011). Radiance images were atmospherically modified and altered into covering the reflectance by by means of Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH).

Table 3.2: Spectral and spatial bands of Sentinel-2 MSI and Landsat 8 OLI, (Sourced: Ngadze et al., 2020).

Sentinel-2 MSI bands			**Landsat 8 OLI bands**		
Bands (m)	**Wavelength (um)**	**Label**	**(m)Bands**	**Wavelength (um)**	**Label**
B1 (60)	0.443	Coastal Aerosol	(30) B1	0.43-0.45	Coastal Aerosol
B2 (10)	0.490	Blue	(30) B2	0.45-0.51	Blue
B3 (10)	0.560	Green	(30) B3	0.53-0.59	Green
B4 (10)	0.665	Red	(30) B4	0.64-067	Red
B5 (20)	0.705	Red Edge 1	(30) B5	0.85-0.88	Near Infrared
B6 (20)	0.740	Red Edge 2	(30) B6	1.57-1.65	SWIR1
B7 (20)	0.783	Red Edge 3	(30) B7	2.11-2.29	SWIR2
B8 (10)	0.842	Near Infrared	(15) B8	0.50-0.68	Pancromatic
B8A (60)	0.865	Red Edge 4	(30) B9	1.36-1.38	Cirrus
B9 (60)	0.945	Water Vapour	(100) B10	10.60-11.19	Thermal IR1
B10 (60)	1.375	SWIR- Cirrus	(100) B11	11.50-12.51	Thermal IR2
B11 (20)	1.610	SWIR 2			
B12 (20)	2.190	SWIR 3			

Raw digital numbers (DN) were changed to top of atmosphere (TOA) for Landsat 8 data, which is the reflectance values that follows the location. The original Level IC-TOA reflectance values were preserved for sentinel-2 data. The consistent spectral bands presented for both sensors were taken into an account for this progression: Red, Blue, Green,NIR, SWIR-1 and SWIR-2/ The SWIR-2 band in Sentinel-2 imagery derives at a 20m resolution, resolution; hence it was resampled to 10m determination using the adjacent neighbor resampling method. For Sentinel-2 imagery, in view of land use and land cover maps, rationalising has been shown to have greater presentation correlated to upscaling. Consequently, all images were collected to match the study sites. These steps were finalised using the image processing (IMPACT) toolbox from the European Commission using ArcGIS software.

Multi-resolution segmentation, using the three visible bands of the electromagnetic spectrum, was executed in IDRISI software. Furthermore, since the study area is small, and is restricted to cloud cover, it was possible to carry out what is called a visual interpretation to eliminate image objects labelled as clouds and cloud shadows. Apart from being labour exhaustive, a through visual interpretation was taken into consideration through a full automative strategy for study area’s small extent, to escape errors of cloud omission errors that may have led to a incorrect disruption ditectives. The low cloud cover images were also taken into consideration since they could not be excluded.

3.4. Data Analysis.

3.4.1 Random Forest Algoritthm (RF), was used to measure the significance of every band for both Sentinel-2 and Landsat-8 in discriminating the herbaceous grass specie for improved classification accuracy (Adam et al. 2009). RF is an non-parametric method which has been extensively used in the ecology and remote sensing studies. The RF method is a joint method that results the prediction accuracy of the ecological field studies (Grimm. *et al.*, 2008). RF the approach has been shown to provide relatively good accuracy without the danger of overfitting (Shah *et al*., 2019), and was developed to overcome the uncertainty of traditional-based methods. Grimm *et al., (*2008), further explained that RF has successfully been used to avoid the over-fitting errors of Artificial Neural Network (ANN). Similarly, RF is an able method of producing a regression or classification functions from a discrete or continuous datasets, it can deal with a complex relationship between predictors due to the noise and a large amount of data (Vincenzi. *et al.*, 2011). Biau and Scornet (2016), further explains that RF forms each data by using an algorithm through a selection of a random set of variables and a random sample from the calibration data sets **(**Biau and Scornet, 2016).

Furthermore, the bootstrapping approach represents the random that is selected through a sampled subset from the entire dataset used in constructing the decision grass, which also acts in reduction of the predicted error (Belgui and Dragut 2016). This means that the algorithms consisting of the set of random decisions tree, each herbaceous grass contributes to its final classification end result. Adelabu et al., 2014 specifies that, in the random forest algorithm, each tree is grown on a separate training set that is a bootstrap replicate of the original data. And further quoted that the training data are sampled to produce an in-bag partition to build the tree (2/3 of the training data), and a smaller out-of-bag (OOB) partition (1/3 of the training data set) in order to validate the performance from each built tree. In this study, the regression model that was used to estimate herbaceous biomass was the random forest (RF) and was validated using 1000 times of bootstrapping and the sampling points were used to extract reflectance data from Sentinel-2 and Landsat 8 before and after fire images. RF regression was used to build a conversion function through using points from the reference image xr = (xr, yr) as contributions to the RF regression model with polynomial pre-processing.The RF fitted models are not prone tooverfitting and multicollinearity, especially dealing with multiple predictors. The optimization of number of variables needed to predict the grass biomass N was determined through the use of recursive feature selection based on leave-one-out-cross validation (LOOCV) together with the root mean square error (RMSE) by Diaz-Uriarte and Alvarez de Andres, 2006). The implementation of the random forest and validation processes was undertaken as per the process described by (Ramoelo.*et al.*, 2015):

(i) N-tree bootstrap sample Xi (i=bootstrap iteration)are randomly drawn with replacement from original dataset (calibration), each containing approximately 1/3 of the features of the calibration data sets X. The variables not included in Xi are called out-of-bag data (OOB) for that bootstrap sample.

(ii) for each bootstrap sample an un-pruned regression tree is developed with the modification that at each node, 1/3 of the predictor is randomly selected and the best divided among those variables is picked.

(iii) at each bootstrap iteration, the response value for data not included in the bootstrap sample (OOB data) is predicted and averaged over all trees (ntree)

(iv) the importance of each predictor is measured by calculating the percent increase in mean square error when the OOB data for each variable is permuted, while others are unchanged. These variable importance values are then used to rank the predictors in terms of their relationship to response variables. The higher the variable of importance score or value the higher the importance of the particular variable in the model.

The validation of the model was completed using LOOCV due to available sample of not more than 100 size and the RF was chosen because the grass biomass (both predicted and observed) was not normally distributed along the park. The statistic measure of the precise and accurateness in terms of coefficient of determination (R^2) and root mean square error (RMSE) were determined. The non-spatial and spatial relationship between the predicted and and observed herbaceous further understanding was determined through the Spearman rank correlation (Hollander and Wolfe, 1973) and the cross-variogram analysis, was separately (Bivand et al., 2008), implemented in R statistical programming language.

3.5. The results

3.5.1. Descriptive Results

To perform this analysis researcher used a simple statistic analyses from excel spreadsheet. Dry biomass was separated into two groups of which 25% (observed) and 75% (predicted). And the results shows that there is slight mean variation between the predicted (236) and the observed (204) grass biomass (table 3.3). Furthermore for a predicted grass biomass of 75% dry biomass perfomed way better than the observed 25%. This is simple proof that grass is not nomrmally distributed along the park

Table 3.3: Descriptive statistics table for dry Grass Biomass of the observed and predictecd, using Computer (excelsheet) statistics fomula.

Variable	**Max**	**Min**	**Mean/Average**	**StDV**
Observed weighted dry grass Biomass **(25%)**	536	58	204	94
Predicted dry grass Biomass **(75%)**	705	104	236	158

3.5.2. Random Forest (RF) algorithm

The reults shows that Further analysis indicate that the bootstrapped random forest model with Sentinel-2 and Landsat 8 data explained significantly over 80% of the biomass variation, with the relative error that ranges between 24 and 28%. *(*Table 3.4***)***. The R^2 (before fire) value differs slightly for the two data sets (S2 0.92 and L8 0.87) whilst the R^2 (After fire) for the two data sets is equal (0.88). The **P**-value for the two data sets for before and after the fire is <0.05 which showed a strong correlation on the two data sets (Sentinel-2 MSI and Landsat 8 OLI) with the biomass.

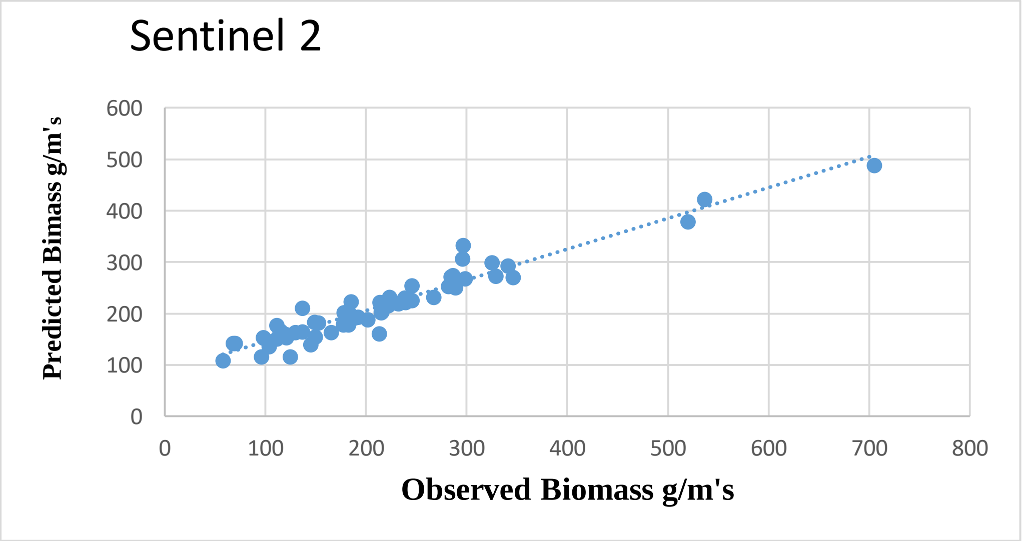
Table 3.4: showing the performance of random forest models for estimating grass biomass using Sentinel-2 and Landsat 8.

	S2B4F	S2AF	L8BF	L8AF
R^2	0.92	0.88	0.87	0.88
R^2adj	0.92	0.88	0.87	0.88
STD error	20.23	23.25	25.76	22.77
RMSE (g/m^2)	50	57	55	58
RRMSE(%)	24	28	26	27
P	<0.05	<0.05	<0.05	<0.05
F-stat	686.9	434.3	392.6	425.8
Optimal bands and VIF	B4, 3, 2, 5, 11	B4, 8, 5	B3, 1, 4	B2, 4, 3, 1

VIF = Variable of Important Factor, and the bands are shown in the order of importance.

The aboveground biomass estimation derived from vegetation indices using Landsat-8 OLI yielded R^2 value of 0.87 for before fire and 0, 88 for after fire, RMSE value of 55 (26%) before fire and 58 (27%) after fire occurrences and Sentinel-2MSI yielded R^2 value of 0.92 before fire and 0.88 after the fire and RMSE value of 50 (24%) and 57 (28%) after the fire. The scatter plot (figure 3.3) provides equations that can be used for the mapping process.

The Red Edge band of Sentinel-2 models became the most important, while near-infrared was the most important in the Landsat 8 based models. Figure 3.4 shows that both models did not predict values over 500 g/m^2, but generally, there is a good fit between modeled and predicted biomass.



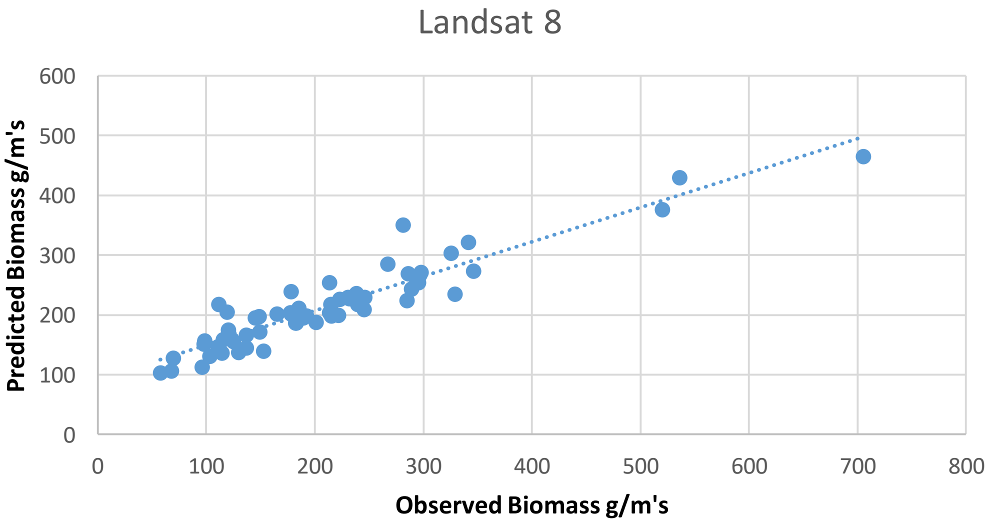


Figure 3.3: Performance of the random forest model for estimating biomass using Sentinel-2 and Landsat 8 data acquired before and after the fire occurrence. (BF= pre or before fire and AF = post or after fire, dotted trend line for the after fire model, and the solid line is the before or pre-fire).

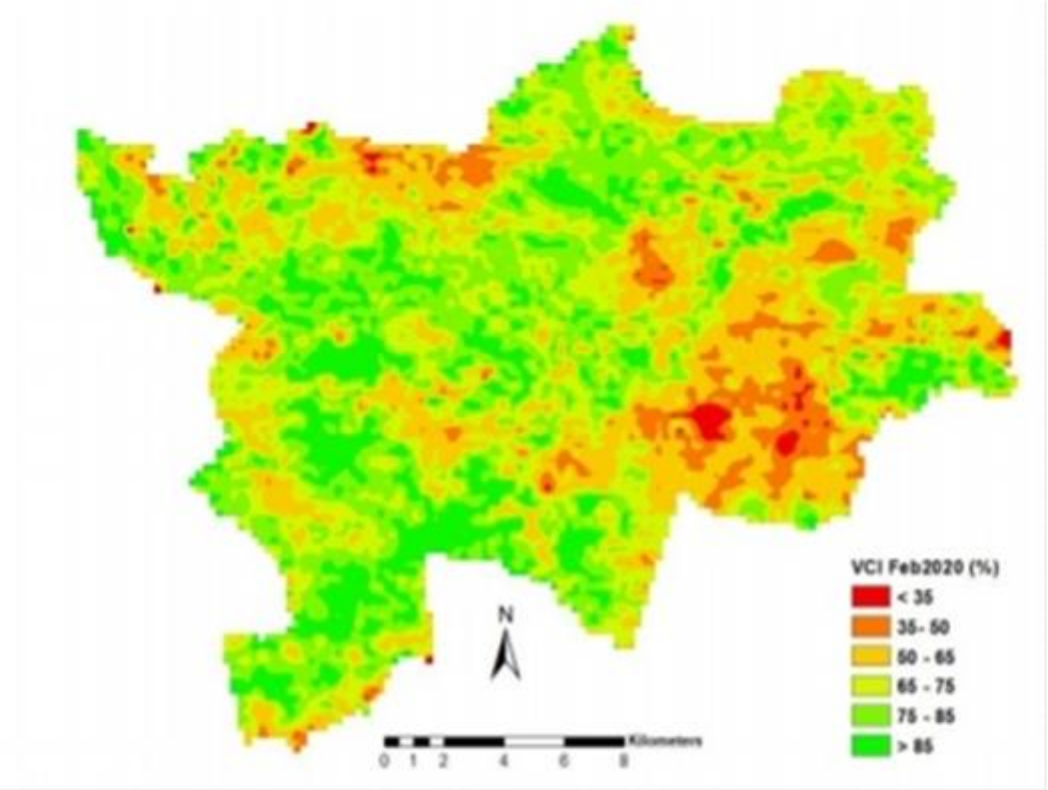


Figure 3.4. The vegetation condition indices map of GGHN Park

There is more vegetation in the lower lands since at higher altitudes harsh environmental conditions generally prevail grass vegetation growth, as indicated by the map.

3.6. Analytical technique

Figure 3.5 (a) and figure 3.5 (b) below show the distribution of grass within the study area, the distribution shown on the histogram assisted in choosing the regression method best suitable for the prediction that was used. The figures show s that there is a precise difference in the mean value for Landsat (before (-9.9) and after (8, 8) fire occurences, but there is absolutely no difference shown by Standard Deviation (StDV) as the values are the same (0.9). On the other hand with sentinel-2 the latter is the other way around, yet still shows the huge difference between the dataset (Sentinel-2 for before and after the fire). The mean for sentinel before the fire (1.9) but for sentinel after the fire (-1.9). The results still show that the StDV (0, 9) for sentinel is still the same on the before and after the fire just like the one for Landsat -8. (See figure 3.6)

Fig 3.5 (a)

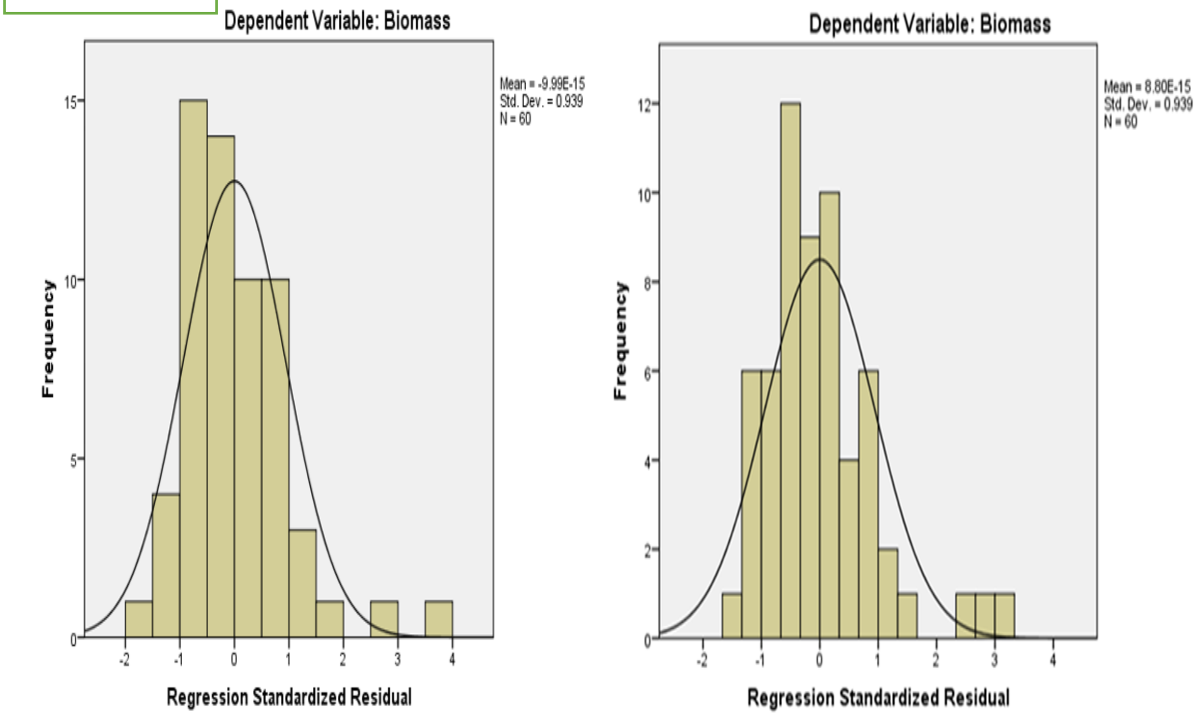


Fig 3.5 (b)

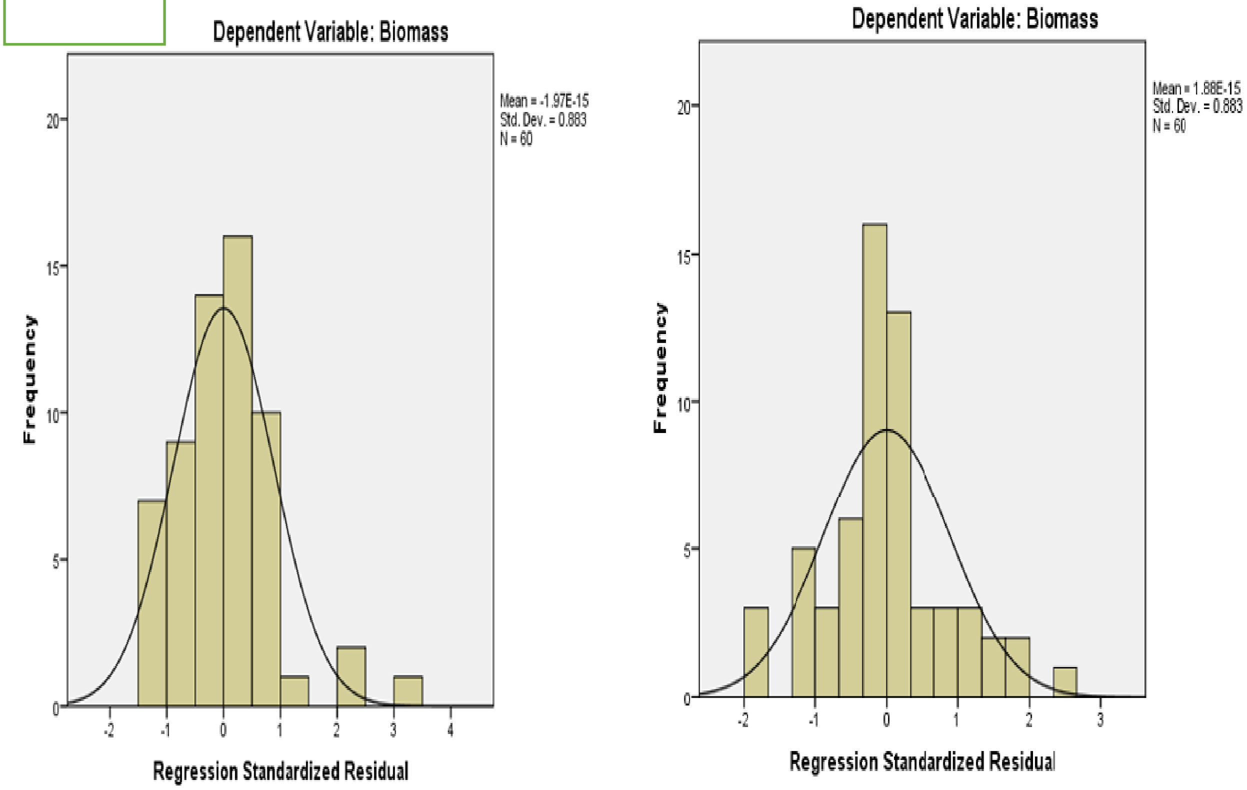


Figure 3.5: Histogram plots of two data sets (a) Landsat 8-OLI and Sentinel-2 MSI (b) for before and after fire occurrence.

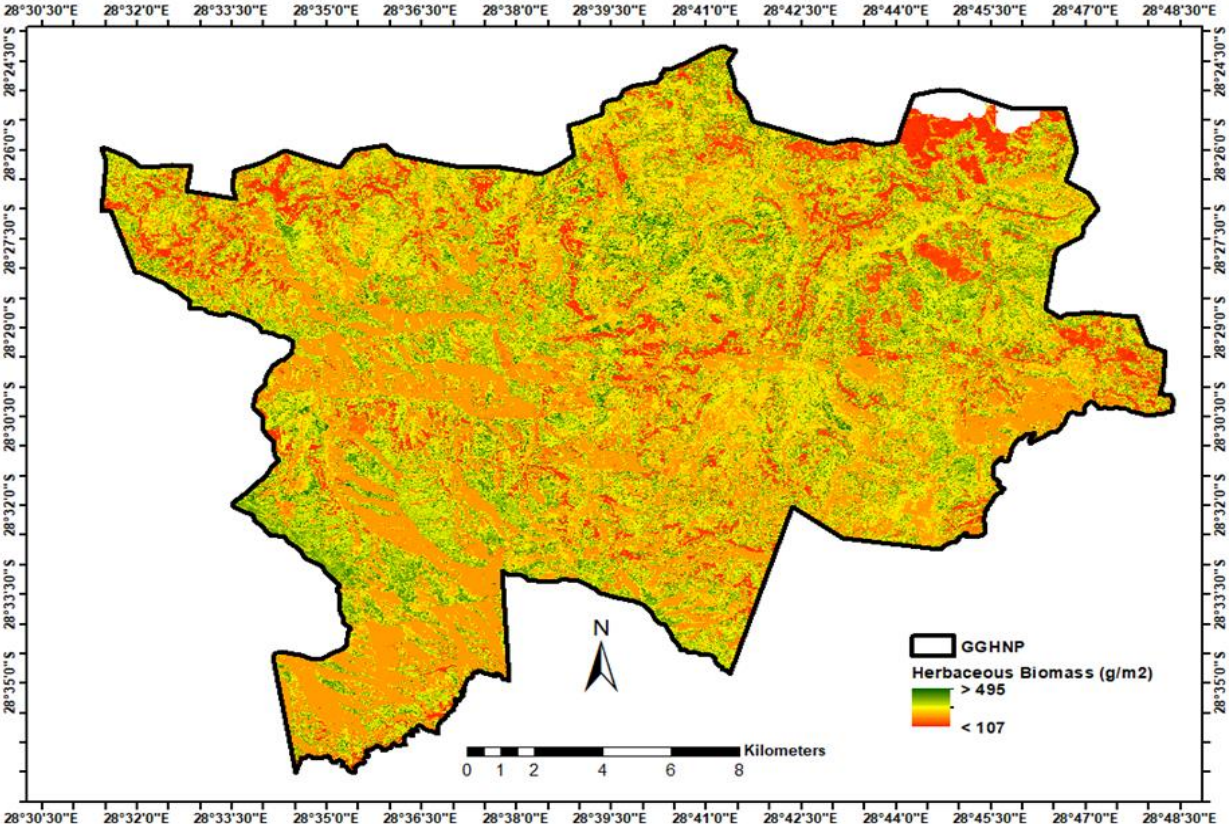


Figure 3.6: Herbaceous biomass index for 2013- 2018.

The Biomass map form the year 2013 to 2018 was joined through change detection analysis in order to determine the overall changes that took place over the years and also to check the grass biomass distribution across the study area. As seen on the map that there is more in the lower parts (S) that is is in the upper parts (N).

3.7. Discusion

In this section, the study set out to at comparing the application of sentinel-2 MSI and Landsat-8 OLI reflectance data to estimate mountainous herbaceous Biomass for before and after Fire occurrence using random forest model. The distribution of the above ground biomass for grass was estimated using a nonlinear regression algorithm. The regression method used to determine a relationship between two variables. Previous studies have explored the potential of random forest (RF) algorithm in modelling the above ground biomass (Silveira *et al.*, 2019, Zeng *et al.*, 2019, Dang *et al.*, 2019, Hu *et al.*, 2016 and Mutanga *et al.*, 2012). To the best of my knowledge, less has been done on mountain grasslands which is the significance of this study. The research used the error rate calculated from the OOB data to perform variable selection with the Random Forest in order to access its effect on the predictive performance on resulting models. For Random Forest Algorithm, out-of-bag OOB method of error rate was calculated to perform variable selection to access its effect on the predictive performance on resulting models. Previous research has shown this to be a statistically complete and efficient approach because the OOB data provide reliable internal estimates of error rate when compared to results derived from cross validation (karlson *et al.*, 2015). The variables (sensors) for before and after yielded an OOB error rate between 24 % to 28% for both sensors' before and after fire with Standard deviation error (StDE) of Sentinel (20.23 and 23.25) and Landsat (25.76 and 22.27) for before and after fire occurrences. Comparing the two multispectral sensors to perform the random forest performed well since the multispectral sensors provides an attractive alternative for estimating aboveground biomass at regional scale especially in areas with limited access to high resolution data and the necessary technical capability. One of their primary pitfalls is the inability to reduce error of estimation (Dube and Mutanga, 2014), this was avoided through using optical bands and VIF (Variable of important factor). In comparing the sensors, the predicted biomass against the observed biomass was modeled for before and after fire occurrences. The results shows that the Red Edge band of Sentinel-2 models became the most important, while near-infrared was the most important in the Landsat 8 based models. This study results were slightly similar to that of Paindit et al., 2018, with the only difference in topography since theirs was conducted at flat topography while this one on different topography since it is a mountainous area. It was noted that the insensitivity of RF to the choice of (N-60) or by using a larger number of grass biomass would have even performed greatest. Even in this absenteeism the Random Forest model offered the powerful alternatives to the traditional parametric classification in both sensors.

Furthermore, the results also showed that both models did not predict values over 500 g/m2, but generally, there is a good fit between modeled and predicted biomass. The observed prediction errors highlighted uncertainty and the limitations associated with mapping the percentage cover using the attributes through optical remote sensing. Main problem for using such optical imagery in area with different topography is that the cloud cover also contributes to the spectral signals and therefore can render the relationship between the sensors and biomass. In a nutshell the reults demonstrated a even through its mountain hills and downfall areas, there is a positive correlation amongst the Above Ground Biomass and the distribution of the herbaceous grass biomass is positively distributed long the park. So therefore, both available sentinel-2 MSI and Landsat-8 OLI multispectral sensors has the ability to detect and map above ground grass biomass but Sentinel-2 perfom better than landsat-8. This is consistent with reults from Meyer *et al.*, (2019), that also showed that sentinel-2 Model perfomed slightly better than Lansat-2 in predicting Leaf Area lndex.

3.8. Conclusion

Based on the random forest results on the two data sets, the estimation of herbaceous biomass is possible in the mountainous areas using both Sentinel-2 and Landsat-8 data. The use of before or after fire yielded a marginal difference in Sentinel-2, but no significant difference in Landsat 8. The random forest model as a machine learning technique presents an opportunity to estimate herbaceous biomass in mountainous environments. Random Forest between these two data sets showed a slight difference in terms of R^2 the sentinel-2 before and after fire varied with 0,4 while Landsat-8 before and after varied with 0,1. The study further indicated that both Sentinel-2 and Landsat-8 provide useful information for grass biomass estimation in mountainous environments. The study concludes that yes the two data set Sentinel and Landsat are useful for estimating the aboveground grass biomass but Sentinel-2 MSI is the one that is used more effectively in mountainous regions for estimating the above-ground biomass since it is an advanced set of new generation sensor. This will help to reach and cover all those areas that are impossible to reach with field-work to help in grass protection and conservation so that there will still be more available grass present in the future to absorb carbon from the atmosphere and also help to control and regulate climate change. When grass is estimated it will also help manage and sustain it to reduce the human activities that will negatively impact them.

Impact of environmental drivers on herbaceous grass biomass through intergration of multi spectral sensors in mountain region.

Chapter 4

Abstract

Mountain area have an extensive variety of social, economic, cultural and environmental benefits that are mostly denoted to as ecosystem services. Environmental variables are essential in determining the distribution of aboveground biomass estimation (AGB). The prediction of biomass models can be acquired through integrating field data with remote sensing and statistical models. This study aims to investigate the impact of environmental drivers on herbaceous grass biomass in a mountainous region through the integration of multispectral sensors. From the results, Biomass did not show any significant difference across herbaceous, dominant grass species and generalized soil types (p>0.05) when tested with Kruskal-Wallis ANOVA. Miscanthus junceus showed no significant difference with biomass for grass type from the rest. However, even though the park consists mostly of silt soil, the results showed a high positive correlation on loam soil with biomass as compared to the rest of other soil types. The results predicted that there has been a low burn severity within the park, which is a good to grass biomass for allowing vegetation plant regeneration and results in a good park management. This clearly shows that the park has currently been in a good or revival state in terms of its fauna and flora.

***Key words**: environmental variables, soil types, ANOVA, topography, elevation*

4.1. Introduction

Mountain area have full extensive variety of social, economic, cultural and environmental benefits that are mostly denoted to as ecosystem services. Like other vegetated grasslands ecosystems, mountains are important blue carbon sinks with large storage capacity (Donato *et al*., 2011). The objective for this study was to determine how the grass biomass is influenced by environmental factors. This can be driven by some activities such as cultivation, exploitation and grazing of the herbaceous grass as a vital instrument of many rangelands that is the source of life for all the organisms that are depending on grass biomass for growth and survival. In many different areas, grass biomass is affected differently by these factors depending on their specific landscape. Mountain regions are one of the landscapes that are mostly affected by these factors (Riebsame *et al*., 1996). The spatial patterns of biomass shape the dynamics of the grassland and its carbon cycle; hence the importance of exploring how biomass is being affected and its response to environmental variations within mountainous areas.

Several studies have been conducted on environmental effects on ecosystem recently, for example, (Buytaert *et al*, 2011, Yang *et al*, 2010, and Pettorelli *et al*., 2005) described how elevation alters mountain vegetation, which hamges the land use and climatic variation and also induces habitat destruction and other human perturbation/ alteration the vegetation in grassland. The increasing demand for agricultural land speed up exploitation and thus leads to soil degradation, overgrazing, overexploitation to mention but few. Fire is one of the principal management mechanisms in the mountain ecosystem, as it interacts with the biophysical environment and its vegetation has shaped the natural landscape of montane area and has further dictated the vegetation species composition and structure for decades (Heinselman, 1981). Fire can have an immediate or long term effect on the ecosystem processes and components, such as plant succession, soil erosion and landscape patterns (Debano, 1991: Verma *et al*., 2019: Freidenreich *et al*., 2020).

Furthermore, topography plays a vital part in the dissemination of herbaceous grass in mountain regions. In most cases, at the stand level, grass aboveground biomass attains their greatest diversity and abundance in the wet tropical mountain ecosystems. In these areas, moderate temperature coupled with constantly high humidity favour the growth of herbaceous grass and accumulation of dead organic matter (Zida *et al*., 2020). In the study conducted by Homeier *et al.*,(2010), it was posited that in many tropical mountains, grass structure changes strikingly from ravines and valley bottom to ridges.

However, due to the steep slopes and relatively high altitudes of hilly landscapes, the vegetation in montane environments has great variation in its species composition of herbaceous layer. Recent studies across the world have examined vegetation species diversity of the mountain chain of different biomes with different landscaping **(**Beever *et al.*, 2008: Finch and Loffler, 2010: Gehrke and Linder 2011: Dirnbock *et al.*, 2003**),** hence this chapter examines the impact of environmental drivers on herbaceous Grass biomass in a mountainous region through integration of multispectral sensors, to further understand how environmental variables influence grass biomass in the mountainous area.

4.2. Study Area

The study area is Golden Gate Highlands National Park situated in the Eastern Free State in South Africa, near the border of Lesotho (Figure 4.1). The park is located within Rooiberge of the Eastern Free State, interior to the Maloti Mountain's foothills, which also includes the Caledon River that forms the periphery of the park's southern part, as well as the margin between the Free State and Lesotho. The uppermost peak within the park is 2,829 m (9,281 ft.) above sea level.

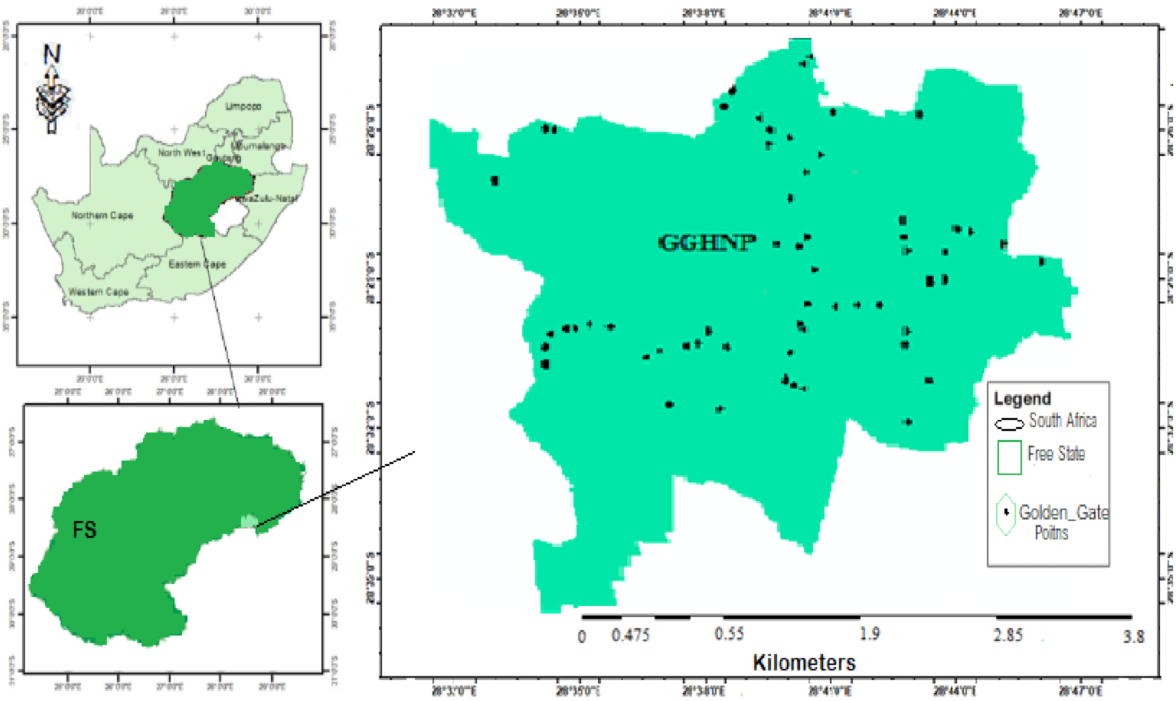


Figure 4.1. Study area Golden Gate Highlands National Park

4.3. Material and Method

4.3.1. Pre-processing and data extraction

Topographic environmental data of topographic wetness, position and ruggedness was extracted together with slope, aspect and DEM from the Aster with 30m resolution. fire frequency from MODIS (250m scale) BAI of the period 2000 – 2007 was extracted aswell for fire severity. Along the environmental data extraction was soil type from field points (60) table 4.1.

Table 4.1: Environmental data extraction

Variables		**Source**	**Scale/ resolution**
Topography	Digital Elevation model (DEM)	Aster	30m
	Slope	Derived from DEM	30m
	Aspect		
	Topographic position index (TPI)		
	Topographic wetness index (TWI)		
	Topographic ruggedness index (TRI)		
Fire severity	Fire frequency	MODIS Burn Area Index (2000-2017)	250m
Soils	Soil type	Field points	60 points

The combined digital elevation model (DEM) data, and the data from meteorology were incorporated to a surface’s fitting at a spatial resolution of 1 km through the use of the extensively used outburst software (ANUSPLIN). The regional application in Golden Gate Highlands National Park grasslands, the spatial data were extracted using the tool (Extract by mask) of ArcGIS (ArcGIS 10.2) software (Environmental Systems Research Institute, Inc., ESRI).

Shuttle Radar Topography Mission (SRTM), the international mission conducted by NASA and the National Geospatial-Intelligence Agency (https://gdex.cr.usgs.gov/gdex/), provides a

DEM product that covers 99.97% of the Earth's land surface, from 28 °S to 28 °N. For this study, the elevation records for Golden Gate Highlands National Park at a resolution of 3″ (90 m) was adopted. The SRTM DEM was resampled to 1000 m resolution so that it can be consistent with the meterological data. Also, slope and aspect were extracted.

Figure 4.2. Field data collection in Golden gate highlands national park. Extracting grass samples.

Seasonal occurrence such as drought (roughness), high rainfalls, absence of clouds and fire were all taken into consideration for the image selection. Elevation data from the SRTM digital elevation model (DEM) (30m resolution) was adopted for this study. Slope and aspect were derived from the DEM covering the area using ArcGIS. Furthermore, three indices were extracted from the DEM, these are topographic position index (TPI), topographic wetness index (TWI) and topographic ruggedness index (TRI).

Area roughness was extracted from ArcGIS. Surface roughness plays a crucial part in microwave remote sensing backscattering and modelling and is a significant factor for research in environmental factors such as hydrological processes soil moisture content and erosion, hence is these research used the method. Mainly, the characterization and representation of land surface roughness is achieved through the height analysis distinctions detected along bisects e.g.,correlation length, root mean square (RMS) height and autocorrelation function (Gharechelou *et al*., 2018). These surface roughness quantities are then executed as inputs for apparent dynamics modelling, e.g., for water or surface runoff estimation, soil erosion modelling and land degradation together with microwave remote sensing scattering modelling and calibration.

4.4. Data Analysis

4.4.1 Correlation Analysis

A non-parametric correlation analysis was adopted because the biomass is not normally distributed, due to the different elevations of the area. Different biomass grows and adapts to different conditions since mountain area is characterized by different elevation, the grass adapts more to favorable condition than unfavorable condition, hence the grass biomass will not be equally distributed, most biomass does favor low temperature, high rainfall, while others are evergreen, they adapt to different weather conditions, hence they are not equally distributed and seek to qualify their correlation with across the areas. Non-parametric Spearman correlation was used due to the fact that it is a method that make use of both continuous and categorical data arrays nonetheless of their numerical scattering and was executed in the R programming language (Hollander and Wolfe, 1973; Lehman, 1998).

4.4.2. ANOVA Analysis

Kruskal –Wallis is used when the analysis of variance (ANOVA) which is the robust test against the normality assumptions is inappropriately used and its homogeneity of variance is violated. The Kruskal-Wallis test is a nonparametric statistical (distribution-free) test that evaluates the difference between three or more individually sampled in sets on a single, non-normally distributed constant variable as it is usually used when the assumptions of one-way ANOVA are not met.

Non-normally distributed data such as rank or ordinal data are suitable for the Kruskal-Wallis test whilst on the other hand the one-way analysis of variance (ANOVA) which is a parametric test, may be executed for typically distributed continuous variables. With the following configuration of the hypothesis to test:

- H_0: population medians or mean are equal.
- H_1: population medians or mean are not equal.

Descriptive statistics, correlation, RMSE, the percentage of RMSE, regression analysis F-test and t-test for two samples, are all the key statiscical analysis method for estimating biomass including Anova (which is also used for this study). The study by Sherali’s equation to test the closeness of dua parameter of tree was adopted to calculating RMSE and RMSE Percentage. Sherali *et al.*, (2003).

RMSE Computation RMSE = $\sqrt{\sum (Yi - \hat{Y})\ 2\ n\ i = 1\ /n}$ ……………………………..(Equation 1)

Percentage of RMSE Computation % RMSE = RMSE * n* 100/ Σ Yi ………..… (Equation 2)

where, RMSE is the root mean squared error

% RMSE representing the percentage of RMSE

Yi representing the inventive value of the dependent variable

Ŷ is the expected value of the dependent variable and

n is the number of annotations.

Application of Kruskal-Wallis Test equation to calculate the null hypothesis

Kruskal-Wallis Formula

$$\mathrm{H} = \frac{12}{n(n+1)} \sum \frac{R_i^2}{n_i} - 3(n+1)$$

…………………………………………..(Equation 3)

Where

n is the total number of points collected

R_i^2 is the for roughness (-0, 29)

n_i is total number of Biomass (1.00)

H= 0,0327

($p>0.05$) when tested with Kruskal-Wallis ANOVA. Therefore we reject the null hypothesis

4.5. Results

4.5.1. Relationship between AGB with Slope

The correlation coefficients concerning the grassland AGB together with the environmental factors, are given in Table 4.2. The results from table 4.2 show that Slope and roughness have a significant negative correlation with herbaceous biomass. An increase in slope giving rise to a decrease in biomass. Thus biomass is inversely proportional to slope. Low lying areas have higher biomass than the steep areas of the park. Ferry *et al.*, 2010, documented that the large trees are therefore shorter downslope as compared to those at the hillstop and slope at a specific diameter, and even shorter in bottomland Bruno, thus, the assumption was that there was a lower productivity of biomass on bottomlands than that on hilltops.

Biomass did not show any significant difference across BAI, dominant grass species and generalized soil types (p>0.05) when tested with Kruskal-Wallis ANOVA.

However, there is a negative correlation between biomass and Roughness, this denotes that as the surface area increases it restrict soil erosion and this has a positive significance in biomass growth. Hence the assumption that roughness is inversely related to biomass but directly proportional to soil erosion rate.

Table 4.2: Spearman rank correlation matrix for biomass and other environmental variables

	Biomass	**Elevation(m)**	**TPI**	**TRI**	**Slope**	**Aspect**	**Roughness**	**TWI**	**Dominant Spp**	**Burnt Area Index**	**Soil Types**
Biomass	1.00										
Elevation(m)	0.05	1.00									
TPI	0.05	0.16	1.00								
TRI	-0.16	0.03	**-0.26**	1.00							
Slope	**-0.32**	0.06	0.00	**0.62**	1.00						
Aspect	0.15	0.02	-0.16	**0.53**	0.14	1.00					
Roughness	**-0.29**	-0.02	-0.20	**0.90**	**0.70**	**0.42**	1.00				
TWI	0.24	-0.17	**-0.51**	-0.16	-0.15	0.07	-0.15	1.00			
Dominant Grass	-0.15	0.12	-0.11	-0.02	0.06	-0.02	0.04	-0.04	1.00		
Burnt Area Index	-0.14	**-0.29**	0.00	0.19	0.19	-0.04	0.13	0.02	-0.09	1.00	
Soil Types	-0.11	0.07	0.01	-0.02	0.17	-0.35	0.07	0.02	-0.02	-0.09	1.00

4.5.2. Relationship between AGB with grass type

From the results below, *Miscanthus junceus* showed high biomass and variability as compared to most of the species types. Whilst *Stiburus conrathii* showed relative lower biomass and variability **(**see Figure 4.3**).** This simply means that the GGNH park consists of much *Miscanthus junceus* than *Seriphium plumosume,* which showed very low biomass and variation. *Miscanthus* can grow on marginal land in relatively cold weather conditions, its carbon dioxide absorption and significant carbon sequestration and high yield make it favorable as a biofuel choice (Xue *et al.,* 2016).

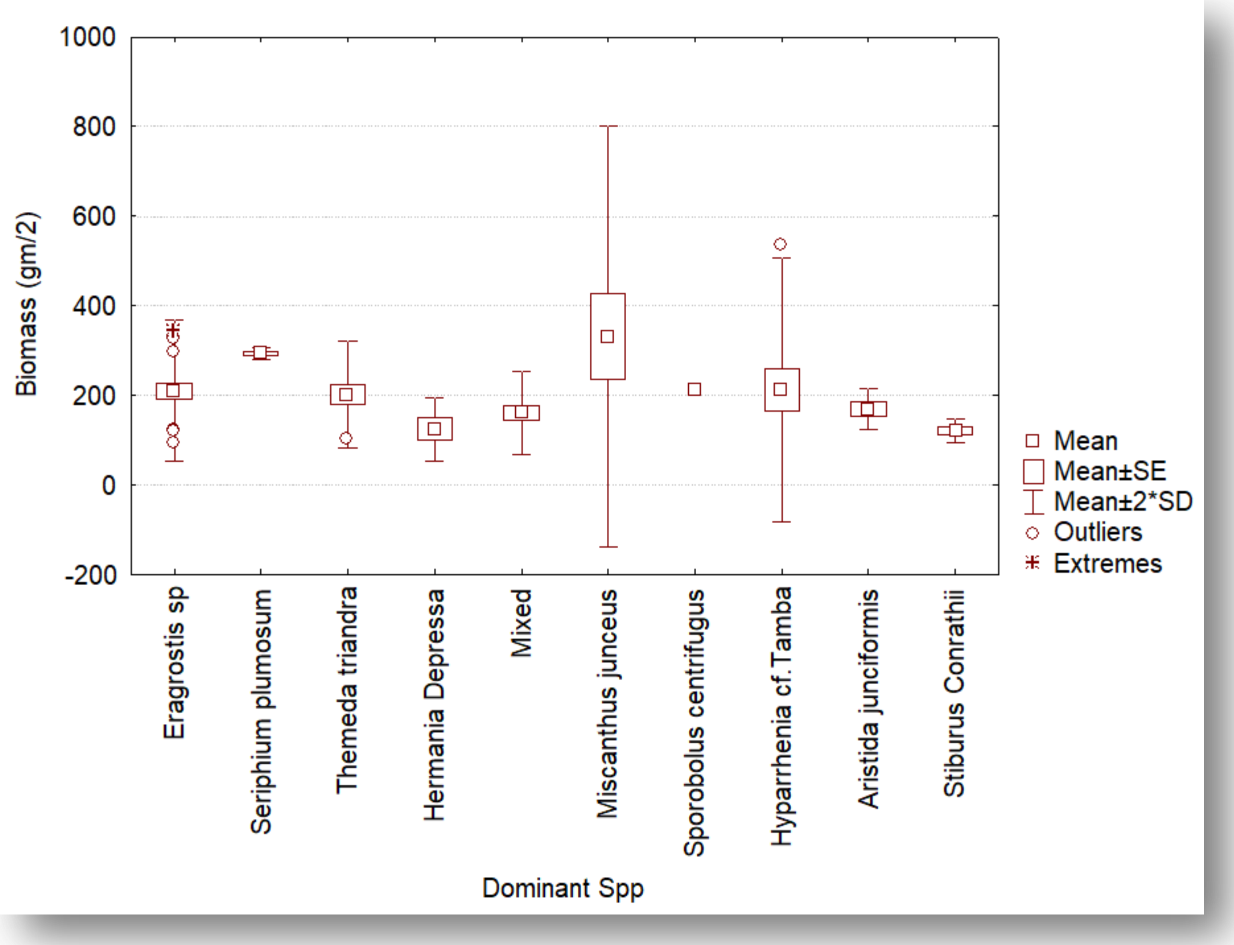


Figure 4.3: Influence of dominant grass types on herbaceous biomass in the mountainous grasslands.

4.5.3. Relationship between AGB with soil texture

Although the park is covered by a high percentage of silt soil than that of loam coverage (Figure 4.5), according to the figure (Figure 4.4), it is evident that loam soil type has a high correlation with biomass as compared to the other three soil types of the park. Silt on the other hand showed a relatively low correlation with biomass. According to Sahu and Raheman, (2006), loam soil is the combination of three main types sand, silt and clay. It generally contains more nutrients, moisture and humus, and it is suitable for growing most plant varieties hence the correlation between loam soil with biomass of the area.

The study showed that there is an increase in the low burnt severity index on herbaceous biomass (Figure 4.6), thus there was an increase to unburnt and decrease in burnt area. Other studies prior to this one has also demonstrated that there is a decrease in burnt area indices.

This has been demonstrated by a recent study (Adagbasa *et al.*, 2019) which indicated that 1120.14 ha has stayed unburned since 2000 probably due to the fact the vegetation contained by the class has adjusted to over time and developed fire resistance, However, about 9859.77 ha has constantly been facing Moderate-low to high severity burn over time and this may be as results of many factors that validate fire ignition and banquet.

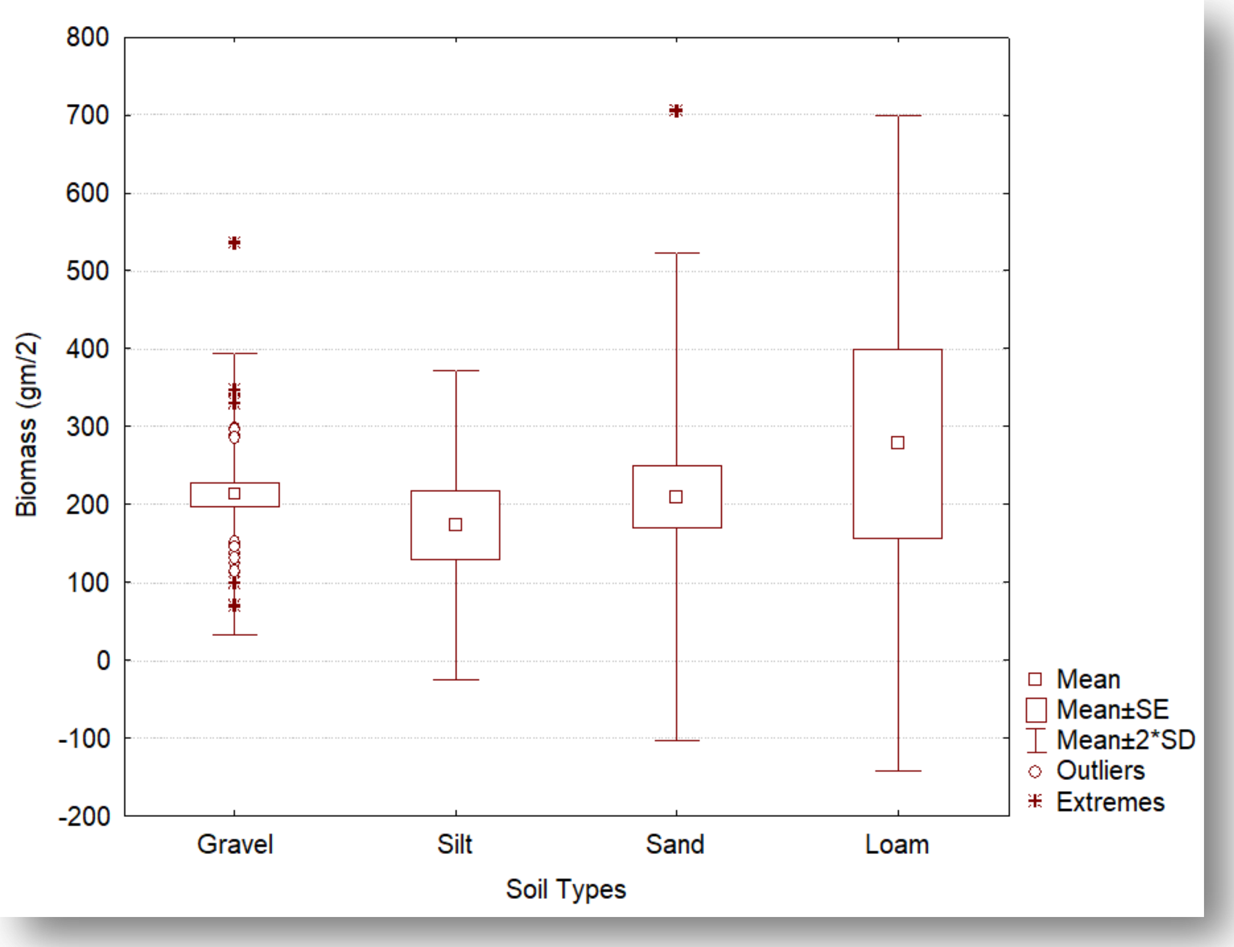


Figure 4.4: Influence of generalized soil types on herbaceous biomass in the mountainous grasslands

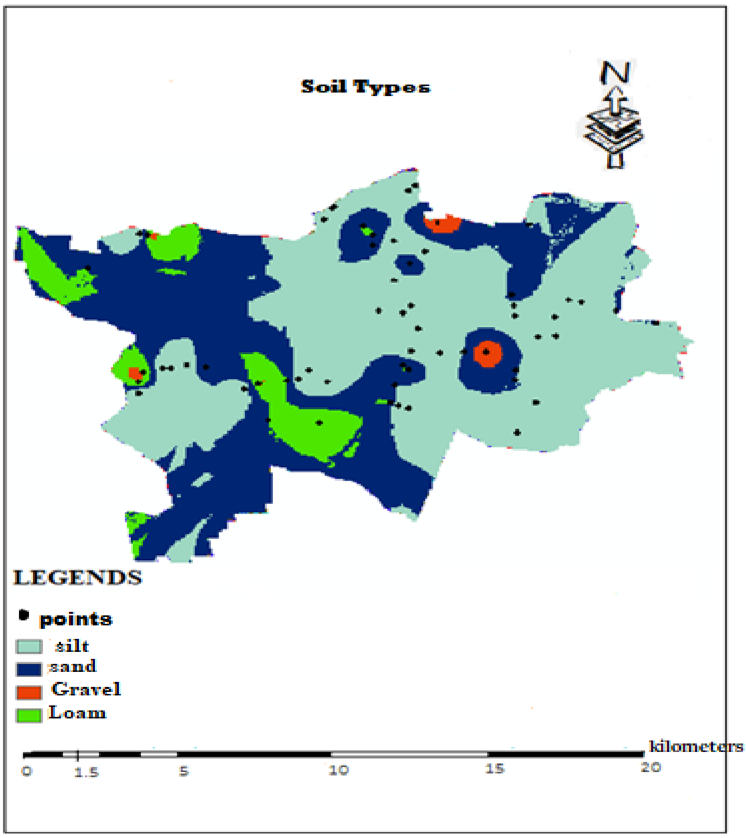


Figure 4.5. The soil map of GGHNP showing the types of soil that is found in the park

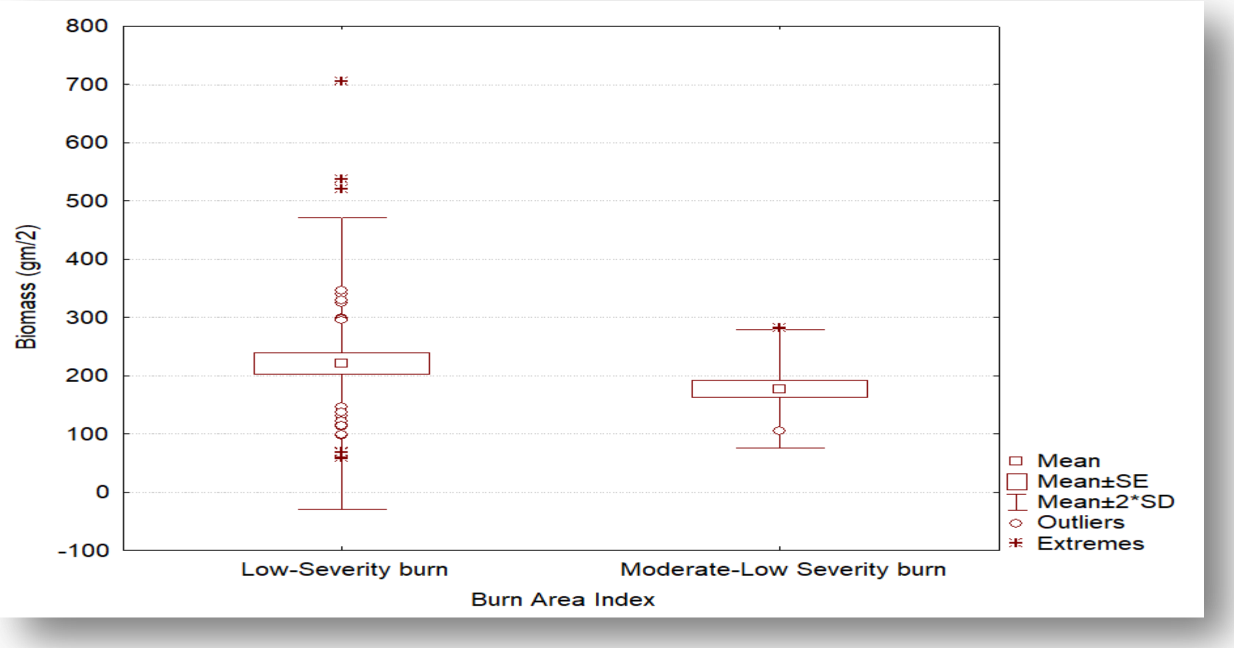


Figure 4.6: Influence of burnt area index (fire) on herbaceous biomass in the mountainous grasslands.

4.6. Discussion

Topographic factors have important impacts on vegetation variations. The combination TRI, Slope and Aspect are significantly and positively correlated with roughness($p<0.05$), whereas there was no significant correlation between Biomass and roughness($p>0.05$). This might reveal the substantial character information about the topographic character of the DEM and how it could be linked to the soil texture. This means that soil is a factor that can influence the growth and abundance of the above ground Biomass. Similar observation were obtained by Sun *et al*., 2013, who argued that soil moisture is a limiting factor for alpine plant growth and production and can also influence the AGB abundance. There has been little literature done on estimating above ground biomass and environmental variables in mountain grasslands, many have focused mainly on grasslands but not mountainous grasslkands (Garcia *et al*.,1993, Calliari *et al*., 2005. Erftemeijer and Herman 1994 and Monteith, 1994). In previous studies, many has reported the significant relationship or correlation between biomass and environmental variables (Baraloto *et al*., 2011: Sun *et al*., 2013: Yang *et al*., 2009 and Schumacher and Roscher, 2008). However, Slik *et al.*, 2010, found that the wood density, stem density, basal area and AGB respond significantly, but differentially to the environment. AGB was only correlated with basal area, but not with stem density and community wood specific gravity. This might be due to different elevation of the area. Topographic effects owing to variations in surface slope angle and aspect also require correction. Instead of using a lambertian approach, the non-lambertian empirical photometric function outlined by Oren and Nayar (1994). The magnitude of the linear distortion depends on the scan angle position of the pixel and the elevation difference with respect to the reference altitude (Itten and Meyer 1993).

In this research results showed that, TWI ia positively correlated to Biomass. Secondary or compound attributes (TWI) are a mixture of both primary attributes that includes a sep,lified equation representing the underlyed physics of natural processes (Schmidt and Persson 2003). This might be that the scale of these environmental variables interconnect hence yielded a positive correlation. Moreover, biomass did not show any significant difference with soil types, dominant species and burn area index (BA) due to the fact that the field data collection was conducted during the dry season that might have impacted the soil type. Biomass did not show any significant difference with dominant grass especially on the south direction. However, the *Miscanthus junceus* grass typer perfomed well influencing the Herbaceous grass biomass in this rearch as compared to other species, whilst *Stiburus conrathii* showed relative lower biomass and variability **(**see Figure 4.3**).** Thus, the dominant grass specie in the Park is *Miscanthus junceus.* Miscanthus junceus also known as Broom grass grows on river banks and vleis, often standing in the water. It is ideally suited to stabilising river banks and probably plays a role in water purification (Mucina et al., 2006: Dingaan, 2008), this is can be due to sufficient or enough soil moisture.

Furthermore, Soil types showed no significant difference with the biomass (table 4.2). however, there was a significant relationship between the Loam soil and herbaceous biomass (figure 4.4). The results are consistent with some previous studies moisture on the lower slope position was significantly higher than that in the upper and middle slopes and had a significant increase trend with slope and was higher on the altitude of 2400–2430 m than in other altitudes (Yuan *et al*., 2019:Sanaei *et al*., 2028: Zha and Li, 2017). Consistent study by Yuan, indicates that soil moisture is a key factor in affecting the aboveground biomass of lucerne and mainly influenced by slope position and slope (Yuan, 2017: Yuan *et al*., 2019 and Yuan *et al*., 2020). In this study the results showed that fire also play a significant role in Hergaceous grass distribution. The results showed that there was a negative correlation between burnt area with biomass and Elevation (table 4.2). howeve, the results in (figure 4.6) shows the significant relationship between Low- sebverity burn and Herbaceous biomass. This is due to the fact that there has been less fire occurences in the park for the past few years, the reults are consistent with other studies (Adagbasa *et al*., 2018 and Savadogo *et al*., 2008).

4.7. Conclusion

The environmental variables do play a major role in distributing the biomass grass together with its growth. The environmental variables do specify which grass type grows where and how and to which height do they grow up to. Currently, the issue of the fire has been of a little occurrence and that makes it so easy for grass to grow. Due to water scarcity, the surface area becomes so rough and thus affects the growth of biomass especially in the hills than at lower lying of the area.

Chapter 5

SYNTHESIS AND RECOMMENDATIONS

5.1. Conclusion

5.1.1. Montane grasslands and biomass estimation using remote sensing techniques

The climate within mountain areas is normally sub-tropical with clear altitudinal gradients in rainfall, wind or air temperature, cloudiness and air humidity conditions. Mountain regions are covered by the diversity of vegetation kinds that are largely unique to their environments and some of these grasses are yet to be fully classified and identified especially in Africa. Herbaceous mountain areas are largely inaccessible due to obvious reasons (e.g. elevation) which make it difficult to overcome. However, remote sensing platforms offer a solution since it is a technology that offers details in definite high determinations and free topographic conditions.

5.1.2. Comparing the application of sentinel-2 and Landsat 8 reflectance data in estimating mountainous herbaceous biomass before and after fire using random forest modelling

Test and match the application of sentinel-2 MSI and Landsat 8 OLI reflectance data in assessing mountainous herbaceous biomass before and after fire using random forest modelling was done. Although this two multispectral sensors provided accurate assessment of the grass above-ground biomass of the study area, these multispectral sensors provide the alternative for estimating aboveground for grass biomass at broad scale specifically in areas with restricted access to high-resolution data and the required technical capability, with one of its primary challenges being its inability to lessen the error of estimation (Dube and Mutanga, 2015).

The performance of the Sentinel-2 in achieving accurate estimation biomass is attributed to the red edge band (band 5). The red edge is known to minimize the biomass saturation problem and influence the transferability of models (Cho. *et al*, 2007). The models did not predict well values over 500 g/m2 because of the limited sampling size covering that range. On the other hand, the performance of the Landsat 8 reflectance was due to the near-infrared band and red, consistently selected by the variable of importance for prediction (VIP). Band 3 (red) and Band 4 (near-infrared are related to pigments such as chlorophyll and the structure of the leaf, respectively. The latter are critical components of the biomass. The performance of the random forest model is due to its non-parametric nature that enables it to fit into multiple predictors with limited overfitting and multicollinearity, especially, when well-parameterized (Ramoelo. *et al*, 2015). The distribution of the above-ground biomass for the grassland was estimated using a nonlinear regression algorithm. The regression method was used to regulate a connection between two variables (predicted grass biomass and observed grass-biomass) that are acquired. And was used as an algo1rithm to enable the development of the prediction models used in the study.

The above-ground biomass grass map from the year 2004 to 2018 was jointly created using the detection analysis to determine the distribution of the grass to also check the changes in grass biomass that have occurred over five years. Both Landsat-8 OLI and Sentinel-2 MSI data attained from the protected unit were selected for mapping aboveground biomass in GGHNP. The results displayed that the distribution of the grass biomass across the area is positively distributed since the p-value of the two datasets Landsat-8 OLI and Sentinel-2 MSI. This means that the grass biomass is equally distributed in the area regardless of the factors contributing to its growth and survival. Even when both natural factors (droughts, fire) and man-made (over-exploitation, over-grazing) has negatively impacted on the growth of the grass biomass, it may be the fact that the grass AGB has adapted to methods or mechanisms to survive even through such factors. Even though this has been a case, some parts of the area have experienced above-average to high.

These two data sets sensors were selected for mapping the grass AGB as the overall estimation of the AGB of the study area, of which they yielded high R^2 values and average RMSE, RMSE %. The imageries were acquired from USGS, to help identify and classify the land covers of our study area. The supervision classification method was used based on the maximum likelihood classification algorithm. To distinguish the different land covers inside the study area, the grass AGB distribution of the study area and how they have been changed over time. This is evident from the patches observed in the study area.

The equation accrued from the mixture of image bands and vegetation indices of the non-protected unit was used in ArcGIS to produce the map display of the distribution of biomass across the study area. Figure 8 shows the quantity of biomass from the highest to the lowest quantity within the region. Fire and nature of the landscape (mountainous) is important for the estimation and understanding of the spatial distribution of biomass. Fire reduces moribund and improves regeneration and quality of the grass (Schepers. *et al*, 2014, Strydom and Savage, 2016). Other factors that could have possibly influenced the results are the ratio of dry/green cover, steepness of the terrain and linking field measurements and satellite data (Shi-Long *et al*, 2004).

Furthermore, the study showed that the grass distributions are overrated in the lower lines than the upper contour.Simply because there are abundant vegetation [grass (AGB)] spiece in the lower areas than the upper areas , due to eits wetness. After all, the area is believed to be wet and rich in soil nutrients. The study also proves that there is more and good biomass in the drainage, this is simply because drainage areas are rich in nutrients and other factors that allow the vegetation to grow.

It is clear that in the rocky areas there is less biomass, as the rocks impede the growth of the biomass, and therefore there is less soil and water contents in rocky areas than there is in the low lining. The rocky areas are also believed to be dry and are causing a blockage for vegetation (grass AGB) to grow naturally. However, there are those plants, that do not require too much water and have acclimatized to the rocky areas that we can find in such areas. This means that grasses that require much water do not survive in rocky areas, but they are found in low lying areas.

5.1.3. Impact of environmental drivers on herbaceous grass in the montane region through integrations of Multispectral sensor.

Constructed from random forest results of the two data groups, the estimation of herbaceous biomass is possible in the mountainous areas using both Sentinel-2 and Landsat 8 data. The use of before or after fire yielded a marginal difference in Sentinel-2, but no significant difference in Landsat 8. The random forest model as a machine learning technique presents an opportunity to estimate herbaceous biomass in mountainous environments. Random Forest between these two data sets showed a slight difference in terms of R^2 the sentinel-2 MSI before and after fire varied with 0,4 while Landsat 8 OLI before and after varied with 0,1. The study further indicated that both Sentinel 2 and Landsat 8 provide useful information for grass biomass estimation in mountainous environments and therefore the study concludes that the two data sets are useful for estimating the aboveground grass biomass but Sentinel-2 MSI is the one that is more effective to be used in mountainous regions for estimating the above-ground biomass since it is an advanced set new generation sensor and is able to reach and cover all those areas that are hard reach through fieldwork. This will ensure that there will still be more available grass present in the future to absorb carbon from the atmosphere and also help to control and regulate climate change. When grass is estimated it will also help manage and sustain it to reduce the human activities that will negatively impact them.

5.2. Recommendation

As shown in the chapter 3 results that the two data sets Sentinel and Landsat both performed well with the slight difference of sentinel-2 performing better, it is recommended that the environmental variables should be used as well to check its impact on estimating the above-ground biomass since they also predict the performance and growth of grass especially in the mountain areas with different altitudes. Chapter 4 has synthesised that indeed the environmental variables affect the biomass positively or negatively. This was evident as the loam soil types had a positive correlation with biomass but there was no significant difference for the grass types.

Although the regressions and the distribution map showed that the grass distribution across the study area was positively distributed along the area, factors such as fire (both natural and man-made) and burn severity affects its maximum distribution. Moreover, other factors such as rocks which are expected since it is a mountain area also impedes the growth of grass AGB. The rocky areas are believed and known to have less water and are sometimes too dry, hence less biomass growth in those areas. AGB within these areas (rocky) poses a gap in further investigations as to how AGB for grasses can be continuously monitored and mapped within these sections in the study area.

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