Mapping the spatial variability of foliar C:N ratio in a communal rangeland using remote sensing

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Abstract

Rangelands contribute significantly to livelihoods by providing grazing land, as well as an array of ecological goods and services. However, they are increasingly threatened by among others, alien invasive plant species, climatic variability and injudicious land management. Hence, sustainable use and optimization of rangelands has recently gained attention. Forage nutrients, such as the C:N ratio are valuable indicators of rangeland quality and quantity, and influence rangeland's carrying capacity and grazing distribution. Therefore, understanding the spatial distribution of foliar C:N ratio in rangelands is valuable for implementing strategic grazing plans and management strategies. Recently, remotely sensed data, specifically the readily available multispectral sensors with improved spectral properties have gained popularity in foliar nutrients modelling. Consequently, this study sought to model fine scale foliar C:N ratio in a heterogeneous communal rangeland using the new generation multispectral sensors. Thus, five objectives were established, firstly; a review of remote sensing applications in mapping foliar nutrients in tropical grasslands. The findings show that the monitoring of foliar nutrients in grasslands, particularly in Sub- Sahara Africa, using high spatial resolution sensors has been hindered by prohibitive costs. Hence, readily available multispectral sensors remain the most viable option in mapping forage nutrients in heterogeneous landscapes. Secondly; to leverage on Google Earth Engine cloud computing platform to monitor the foliar C:N ratio in a heterogeneous landscape using Sentinel 2 data and the random forest algorithm. The results show an estimated R^2 accuracy of 74, with RMSE of 2.68 for the validation datasets of the C:N ratio model established by integrating the spectral bands and vegetation indices. Thirdly, the study sought to test the efficacy of fusing Sentinel 2 and Superdove Planetscope datasets in enhancing the rangeland foliar C:N ratio prediction at a landscape scale. The results demonstrate that freely available new generation multispectral sensors with unique spectral settings offer new opportunities for improving forage C:N ratio mapping in resource-poor countries. Using Sentinel 2 data, the study established that the visible, red edge and near infrared regions of the electromagnetic spectrum were influential in predicting the foliar C:N ratio. The study also established that fusing the spatial resolution of Planet scope with the Sentinel 2's spectral properties enhanced foliar C:N ratio estimation within a heterogeneous landscape (R^2 of 0.79 and RMSE of 2.36).Furthermore, the study noted that both Planetscope's high spatial resolution and Sentinel 2 MSI's high spectral resolutions were valuable in determining the spatial variability of foliar C:N ratio and the inclusion of the red edge spectral settings, combining fused datasets with ancillary variables and the adoption of robust algorithms such as Random Forest improved foliar C:N ratio modelling accuracy. Other variables such as wind effect, topographic wetness index, and the sky view factor also influence the foliar C:N ratio spatial variability . Overall, the findings of this study offer new insights on reliable and cost-efficient approaches for mapping forage nutrients in resource-constrained regions such as South Africa. Using freely available advanced multispectral sensors, the study provides valuable information necessary for optimal rangeland management.

Keywords: C:N ratio, Communal rangelands, Remote Sensing, Sentinel 2, Planetscope, Data fusion, Random forest, Topography, Climate.

Preface

The research contained in this thesis was completed by the candidate while based in the Discipline of Geography, School of Agricultural, Earth and Environmental Sciences, of the Collage of Agriculture, Engineering and Science, University of KwaZulu-Natal, Pietermaritzburg Campus, South Africa. The research was financially supported by the National Research Foundation (NRF) of South Africa, Research Chair initiative in Land Use Planning and Management ((SARChI) (Grant Numbers: 84157). The contents of this work have not been submitted in any form to another university and, except where the work of others is acknowledged in the text, the results reported are due to investigations by the candidate.

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

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Declaration 1

Declaration 1: Plagiarism

I, Mariama Adeola Arogoundade declare that:

1. The research reported in this dissertation is my original work unless otherwise indicated.

2. This dissertation has not been submitted for the attainment of a degree or examination purposes at another university.

3. This dissertation does not contain any data, graphics, and other information from other persons unless duly acknowledged.

4. This dissertation does not contain other persons' writings unless duly acknowledged as such. In cases where written sources have been cited;

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5. This dissertation does not contain text, graphics, and or tables directly copied and pasted from the internet unless otherwise sources were duly acknowledged within the content of this dissertation.

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Declaration II: Manuscripts and publication

1) **Arogoundade, A.M.,** Mutanga, O., Odindi, J., R Naicker. The role of remote sensing in tropical grassland nutrient estimation: a review. *Environmental Monitoring and Assessment* 195, 954 (2023).
2) **Arogoundade, A.M.,** Mutanga, O., and Odindi, J. (2023). Leveraging Google Earth Engine to estimate foliar C: N ratio in an African savannah rangeland using Sentinel 2 data. *Remote Sensing Applications: Society and Environment* 30 (2023):100981.
3) **Arogoundade, A.M**., Mutanga, O., and Odindi, J. Fusion of Planetscope and Sentinel 2 in assessing foliar C:N ratio in a rangeland. *Journal of Spatial Science* (2023): 1-23.
4) **Arogoundade, A.M.,** Mutanga, O., and Odindi, J, R, Naicker. A multi-source data approach to mapping C:N ratio within a heterogeneous rangeland.

Signed: M. Adeola Arogoundade Date: 7/02/2024.

Dedication

To HIM who is able to do exceedingly, abundantly more than we can ever ask for.

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Acronyms

AGB	Above ground biomass
ANNs	Artificial Neural Networks
AVIRIS	Airborne visible/infrared imaging spectrometer
C	Carbon
C:N	Carbon to nitrogen ratio
CBC	Carbon-based constituents
CI red-edge	Chlorophyll-red edge based index
DL	Deep learning
DVI	Difference vegetation index
EVI	Enhanced vegetation index
GEE	Google earth engine
GNDVI	Green normalized difference vegetation index
IDE	Integrated Development Environment
IRECI	Inverted red-edge chlorophyll index
LAI	Leaf area index
LMA	Leaf dry mass per unit leaf area
MAE	Mean Absolute Error
ML	Machine learning algorithms
MSRI	Modified simple ratio index
MTCI	MERRIS terrestrial chlorophyll index
MTVI	Modified triangular vegetation index
N	Nitrogen

NDVI	Normalized difference vegetation index
NDVIRE	Red-edge normalized difference vegetation index
NDRE1	Normalized difference red-edge 1
NDRE2	Normalized difference red-edge 2
NDII	Normalized difference infrared index
NIR	Near infrared
NPP	Net primary productivity
NND	Nearest Neighbour Diffusion
OOB	Out-Of-Bag
PLSR	partial least square regression
PS	Planet scope
R^2	Coefficient of determination
RS	Remote sensing
Red edgeCl	Red edge Chlorophyll index
RECI1	Red edge chlorophyll index 1
RF	Random forest
RMSE	Root mean square error
RTM	Radiative transfer model
S2	Sentinel 2
S2REP	Sentinel-2 Red-Edge Position
SMLR	Stepwise multiple linear regression
SR	Simple ratio
SVM	Support vector machine
TVI	Triangular vegetation index

TWI	Topographic wetness index
UAVs	Unmanned Ariel Vehicles
V-R^2	Coefficients of determination of validation
WDRVI	Wide Dynamic Range Vegetation Index

Chapter One: General Introduction

1.1 Introduction

Globally, rangelands cover about 41% of the world's land area, support about 2 billion people, and provide an array of ecological, and socio-economic benefits (Briske et al., 2020, Öborn et al., 2022). Rangelands are an important source of free feed for livestock, particularly in rural communities in developing countries (Cousins, 1999, Hamadeh, 2023). Through the sale and consumption of animal products, smallholder farmers create revenue and improve household nutrition (Samuels et al., 2023). However, approximately 75% of the world's grazing area has been degraded, with a loss of about 25% of its animal carrying capacity (Mudau et al., 2022, Angerer et al., 2023). According to Bangira et al. (2023), in the last 10 years, the global livestock industry has lost more than USD 7 billion due to grassland degradation. Rangeland degradation arising from conflicting land uses, poor land management, invasive species, and extreme weather, results in poor livestock productivity, especially in communal grazing areas (Angerer et al., 2023, Turyasingura et al., 2022). As a result, rangeland degradation is a threat to pastoral communities. Hence, studies that provide informed knowledge can impact policies and legislation pertaining to rangeland management, while creating suitable grazing strategies to maximize rangeland resources. It is therefore important to monitor grassland health/nutrients to understand their impact on grassland productivity and quality.

Forage quality can be inferred from plant nutrients such as nitrogen, carbon-based constituents (starch, lignin, cellulose and sugar), and chlorophyll (Kang et al., 2023, Bangira et al., 2023, Ramoelo et al., 2012a). While theses biochemical properties are crucial in grass development, they are also key indicators of the ecological process and management practices that affect livestock migration and grazing patterns (Yu et al., 2017b, Yu et al., 2017a). Foliar nutrients, such as Carbon (C) and Nitrogen (N) are key elements in the development and productivity of rangelands (Liu et al., 2022b, Raines, 2011). Essentially, N is a major component of chlorophyll, necessary for plant productivity**,** while C is important in the building of plant tissues (Mu and Chen, 2021). Thus, nitrogen availability has been established to drive the photosynthetic process, plant physiological development and carbon generation (McAllister et al., 2012). Therefore, changes in nitrogen levels can alter the rate of C conversion in plants during photosynthesis (Liao et al., 2008). Foliar stoichiometry ratios such as the C:N ratio are important in plant and climate change studies, because they incorporate both plant physiological and molecular responses to stress (Yan et al., 2015). The C:N ratio is an indicator of plant response to climate change, nutrient use efficiency and soil organic matter, which are critical in precision livestock farming (Wang et al., 2021a, Sun et al., 2020b). Also, the C:N ratio is a measurable landscape-scale indicator of vegetation quality that has the potential to improve regional estimates of net primary productivity (NPP) by providing real-time C:N ratio values at a landscape scale (Phillips et al., 2006, Caldararu et al., 2020). A review of different studies revealed that foliar C:N ratio values between 20 and 30 indicate high-quality forage, while values < 20 or >30 indicate poor-quality forage (Berri, 2007, Phillips et al., 2006, Gao et al., 2020a). For instance, in the Northern Great Plains rangelands, Phillips et al. (2006) reported high- quality forage (a lower C:N ratio) in fertilized grasses (23 ± 4.4), in contrast to a higher C:N ratio (poor-quality forage) for extremely grazed pastures (31.3 ± 4.4). In the northern mixed-grass prairie, Beeri et al. (2007) noted that grazing animals require low C:N ratio < 36, with high protein contents. However, it should be noted that these studies were conducted in different environments, hence the differences in the values of forage C:N ratio. To better understand livestock grazing distribution, and enhance rangeland management practices, it is important to accurately and timely assess the spatial variability of C:N ratio in rangelands.

The traditional methods of estimating plant nutrients such as N and C in vegetation are dominated by field measurements and laboratory techniques (Muñoz-Huerta et al., 2013, Murguzur et al., 2019). Although these approaches are highly precise, they are expensive, time-consuming, and challenging in difficult terrains (Arogoundade et al., 2023d, Xu et al., 2023). In contrast, remote sensing (RS), is a cost effective and an invaluable spatio-temporal source of information on foliar nutrients such as C:N ratio in rangelands (Sibanda et al., 2021, Berri, 2007, Kang et al., 2023). Also, the high spatial and spectral resolutions of remotely sensed data, can distinguish features with comparable features in vegetation (Minaei et al., 2022, Zhang et al., 2023), especially at a landscape scale. Whereas, prior works have utilized remote sensing in monitoring N and C in grass (Peerbhay et al., 2022, Naicker et al., 2023, Ramoelo et al., 2012b), few studies have estimated the C:N ratio in rangelands. For instance, Gao et al. (2020a) used hyperspectral data to predict C:N ratio in the alpine grassland with an accuracy of 85 to 92%. Similarly, in mixed grassland, Beeri et al. (2007) retrieved forage C:N ratio with a relative error of 8% in a mixed grassland in North Dakota. In another study, Phillips et al. (2006) estimated the C:N ratio in Northern Great Plains rangelands utilizing the convectional broad band sensors (Landsat 5 and ASTER) with an RMSE of 3.1 and 1.5, respectively. Nonetheless, these sensors are either prohibitively expensive and limited to plot scale (hyperspectral data), or the spatial resolutions (Landsat 5) are too coarse to retrieve foliar C:N ratio in the rangeland due to grasslands complexity and heterogeneity, especially at a landscape scale (Powell et al., 2007, Pandey et al., 2020).

The advent of modern generation multispectral sensors such as Sentinel 2, Rapid Eye and Super dove Planet scope, with improved radiometric, spatial, spectral and temporal resolutions, offers novel opportunities to map foliar nutrients such as the C:N ratio in rangelands, while addressing the limitations inherent in traditional sensors (Pereira et al., 2022, Loozen et al., 2019). These sensors are cost effective, readily available and, are characterized by strategically located red edge bands that are valuable for improving the detection and mapping of foliar nutrients in rangelands (Mutanga et al., 2015, Ramoelo et al., 2012b, Sibanda et al., 2015). Specifically, Sentinel 2 MSI has gained considerable interest due to its open access policy, medium spatial resolution (10m, 20m and 60m), 5 days temporal cycle, 13 spectral bands and larger swath width of 290 km; facilitating landscape and regional monitoring of rangeland nutrients (Gao et al., 2020b, Abdullah et al., 2019). Sentinel 2 MSI has three red edge bands- 705, 740 and 775nm that have been shown to improve the detection of foliar biochemical and biophysical properties in plants (Belgiu et al., 2023, Arogoundade et al., 2023d). The red edge region is highly sensitive to plant biochemical and biophysical properties such as nitrogen, lignin, chlorophyll, cellulose, leaf area index, and biomass (Madonsela et al., 2022, Abdullah et al., 2019). Despite the sensor's popularity, its strength and the application of the red edge position have not been fully explored in monitoring foliar C:N ratio within heterogeneous grassland at a landscape scale.

Cloud based platforms such as the Google Earth Engine (GEE) provide free access to global satellite images in vegetation mapping, thus allowing intensive computation analysis (Tsai et al., 2018). The GEE is an efficient powerful data processing platform which allows developers to analyse, visualize and store data in cloud via the web-based Integrated Development Environment (IDE) code editor (Alencar et al., 2020). While GEE supports the processing of large volumes of remotely sensed imagery, it permits the user to compute different machine learning applications, while pre-viewing the results in real time (Tsai et al., 2018). Thus, GEE provides an opportunity to monitor the spatial patterns of forage C:N ratio efficiently and in real time.

Nevertheless, optical sensors suffer from clouding effects, and are often limited by their spatial, temporal, radiometric and spectral resolutions (Prudente et al., 2020, Xie et al., 2008). For example, the medium spatial resolutions of Sentinel 2 (10m, 20m and 60m) may not detect the changes in the spatial variation of foliar C:N ratio in small patches of grass (Arogoundade et al., 2023a). However, the high spatial resolution of Superdove Planet scope sensor (3m) can overcome such challenges (Zhao et al., 2022, Kluczek et al., 2023), by enhancing the spatial resolution of Sentinel 2MSI in estimating the foliar C:N ratio in heterogeneous grassland at a landscape scale. Hence, there is a need to evaluate the efficacy of fusing optical sensors to improve the prediction accuracy of the C:N ratio in heterogeneous landscapes at a fine scale, while mitigating the constraints of each sensor. Furthermore, forage nutrients in rangeland are controlled by different abiotic and biotic factors which include elevation, temperature, precipitation, soil nutrients, grazing and solar radiation (Lu et al., 2023, Tang et al., 2022). The interaction of these factors individually or collectively results in a patchy distribution of pasture nutrients on the landscape composed of various grass species (Teague and Dowhower, 2003, Wang et al., 2020). While prior works examined how topographic and climatic variables affect foliar N and C estimation in grasslands, little is known about the precise factors affecting the spatial distribution of foliar C:N ratio, especially within KwaZulu-Natal's distinctive and biodiverse rangelands. Therefore, a deeper knowledge on the influence of environmental variables on the geographical distribution of foliar C:N ratio is required, particularly in the light of climate and land use changes. In addition, Knox et al. (2012), Ramoelo et al. (2013), and Ramoelo and Cho (2018) reported that integrating site-specific topo-climatic data with optical imagery enhances the accuracies of prediction models in mapping foliar nutrients. Therefore, using multisource data can further improve the estimation of foliar C:N ratio in the rangeland.

Different studies have shown that remotely sensed data tend to be highly correlated, which can limit the performance of predictive models in estimating foliar nutrients such as the C:N ratio in rangelands (Arogoundade et al., 2023b, Vasudeva et al., 2021). As such, robust machine learning algorithms that can effectively improve the estimation of foliar C:N ratio is required. Non-linear machine learning, such as the random forest regression has been employed in various vegetation studies due to its superior performance in handling multi-collinearity between predictor variables (Breiman, 2001c, Choudhary et al., 2022). Also, the random forest algorithm can optimize model performance by tuning the parameters the number of trees (*Ntree*) and the number of random variables in each tree (*Mtry*) (Probst et al., 2019), as well as ranking predictor variables in terms of importance (Choudhary et al., 2022). In this regard, the use of random forest in estimating foliar C:N ratio in heterogeneous landscapes is very promising.

1.2 Aim

The aim of the study was to assess the performance of new generation multispectral sensors with ancillary data in mapping and predicting foliar C:N ratio distribution in the communal rangelands of Vulindlela, KwaZulu-Natal, South Africa.

1.3 Objectives

1) To provide an overview on the progress of remote sensing techniques and machine learning algorithms in predicting the C:N ratio in a rangeland.
2) To leverage the use of Google Earth Engine (GEE) clouding computing platform with Sentinel 2 datasets and the random forest algorithm in retrieving the C:N ratio.
3) To test the efficacy of fusing Planetscope and Sentinel 2 MSI datasets, as well as compare the trade-off between the sensors in foliar C:N ratio estimation in a communal rangeland.
4) To explore the utility of topo-climatic variables integrated with fused datasets in enhancing the prediction accuracy of foliar C:N ratio at a landscape scale.

1.4 Study site

The study area is within Vulindela communal rangeland, west of the city of Pietermaritzburg, in KwaZulu Natal Province, South Africa at 29°.40′37.3584″ S and 30°.8′13.6572″ E (Figure 1). The average precipitation in the area ranges between 900 to 1000mm, while the mean annual temperature is 21.9°C. The area is characterized by undulating topography. Loamy soils are usually found in valley sides, while coarse-grained soils are found on higher slopes due to rocky terrain (Masenyama et al., 2023). According to Scott-Shaw and Escott (2011), *Themeda triandra* grasses, which are forb-rich, and bitter, used to dominate the area. However, due to the region's lengthy history of plant invasion, the local vegetation has undergone significant change and is now primarily made up of mesic grasses of different species (Scott-Shaw and Escott, 2011). These grasses include; *T. triandra, Paspalum urvillei*, *Tristachya leucothrix and Sorghum bicolour.* Livestock farming is the main source of income in Vulindlela, and residents rely on grasslands as grazing areas for their livestock.

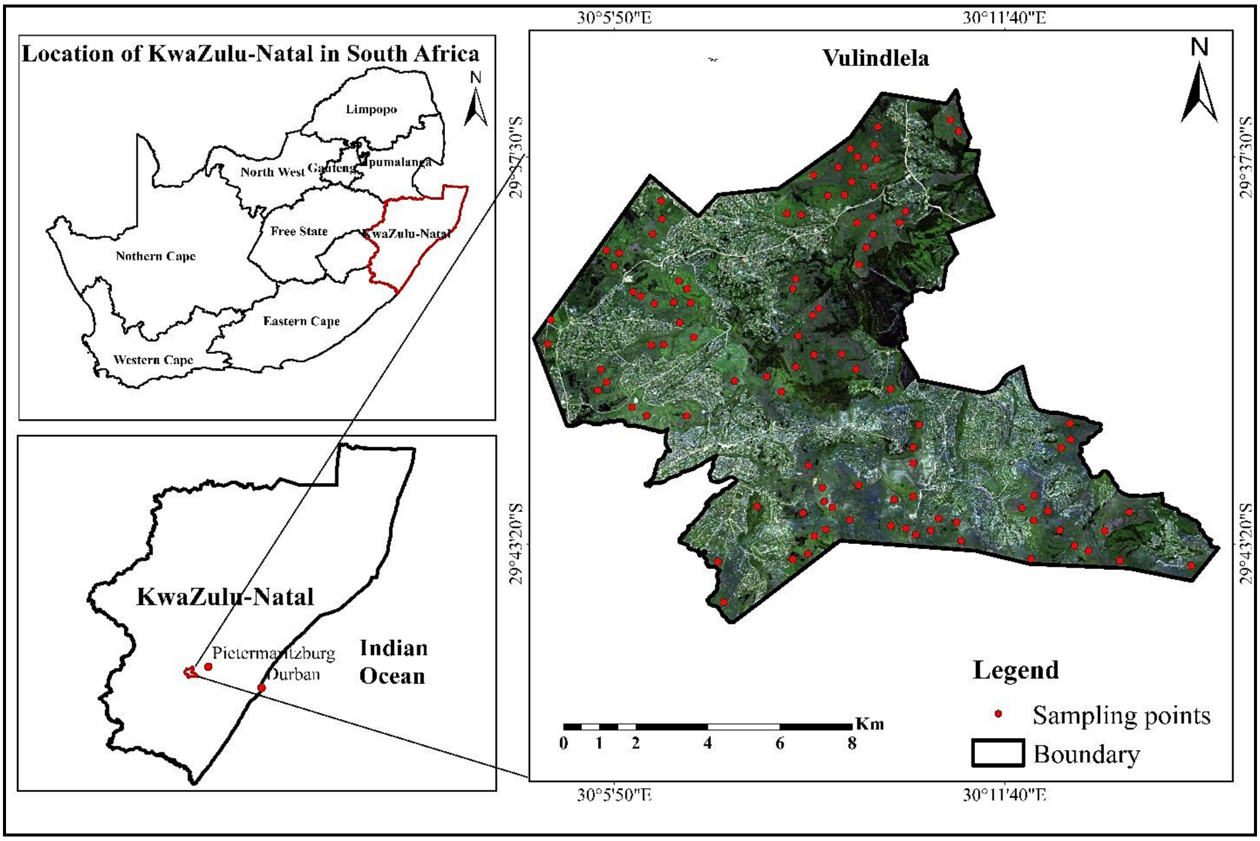

Figure 1:1: The study area showing sampling points for the C:N ratio.
Source: Sentinel 2 multispectral imagery from the European Space Agency`

1.5 General structure of the thesis

This thesis consists of five research papers that address each of the study objectives listed in section 1.3, excluding the general introduction in chapter 1 and the synthesis in chapter 7. The literature review and methodologies are entrenched within the mentioned papers.

Chapter Two: This chapter provides a comprehensive review of the advancements in remote sensing technology, limitations, and emerging opportunities in mapping the C:N ratio in rangelands. In this paper, we focused on multispectral and hyperspectral sensors while investigating their spectral properties, absorption features, empirical and physical techniques, and algorithms in predicting the C:N ratio in grasslands. Limitations and recommendations were examined, as well as future prospects on the use remotely sensed data in predicting foliar nutrients in grasslands. It also emphasized the research gaps, and the need to embrace cost effective techniques for mapping and monitoring rangeland quality in resource constrained countries like South Africa.

Chapter Three: Having identified the need for readily available remotely sensed datasets and efficient techniques for monitoring rangeland health in resource constrained regions**,** this chapter leveraged the use of the GEE cloud computing platform to test the efficacy of Sentinel 2 datasets and the random forest algorithm in mapping the spatial variability of the C:N ratio in the rangeland. Thus, this chapter examined the potential of freely available Sentinel 2 MSI characterized by medium-to-fine spatial resolutions with strategically position red edge region in the electromagnetic spectrum in mapping the foliar C:N ratio in a communal rangeland. The integration of bands and vegetation indices from the unique spectral settings were examined in estimating the C:N ratio.

Chapter Four: This chapter evaluated the efficacy of fusing Sentinel 2 and Planetscope to enhance the prediction of foliar C:N ratio in a heterogeneous landscape. This study elaborated on the value of fusing high spatial Planetscope and high spectral Sentinel 2 data in improving prediction accuracy of foliar C:N ratio in a heterogeneous landscape. Furthermore, we examined the efficacy of Planetscope and Sentinel 2 datasets in predicting the C:N ratio in the study area based on their spatial and spectral properties. Finally, the most relevant variables for predicting the C:N ratio within the rangeland were identified using Sentinel 2, Planet Scope, and fused images.

Chapter Five: this chapter focused on the use of remotely sensed and ancillary data in estimating forage C:N ratio. This chapter compared the accuracies between multisource (integration of environmental and fused datasets) and fused datasets in predicting the C:N ratio in the rangeland. Also, a detailed explanation of the impact of environmental variables in the spatial distribution of foliar C:N ratio is presented.

Chapter Six: This chapter provides a synthesis of the findings of the preceding five chapters in this research in mapping forage C:N ratio at a landscape scale. The section concludes by outlining the limitations, and future recommendation in forage quality assessment using remotely sensed techniques. Lastly, a single reference list is provided at the end of the thesis.

Chapter Two: The role of remote sensing in tropical grassland nutrient estimation: a review

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REVIEW

The role of remote sensing in tropical grassland nutrient estimation: a review

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Abstract

The carbon (C) and nitrogen (N) ratio is a key indicator of nutrient utilization and limitations in rangelands. To understand the distribution of herbivores and grazing patterns, information on grass quality and quantity is important. In heterogeneous environments, remote sensing offers a timely, economical, and effective method for assessing foliar biochemical ratios at varying spatial and temporal scales. Hence, this study provides a synopsis of the advancement in remote sensing technology, limitations, and emerging opportunities in mapping the C:N ratio in rangelands. Specifically, the paper focuses on multispectral and hyperspectral sensors and investigates their properties, absorption features, empirical and physical methods, and algorithms in predicting the C:N ratio in grasslands. Literature shows that the determination of the C:N ratio in grasslands is not in line with developments in remote sensing technologies. Thus, the use of advanced and freely available sensors with improved spectral and spatial properties such as Sentinel 2 and Landsat 8/9 with sophisticated algorithms may provide new opportunities to estimate C:N ratio in grasslands at regional scales, especially in developing countries. Spectral bands in the near-infrared, shortwave infrared, red and red edge have been identified to predict the C:N ratio in plants. New indices developed from recent multispectral satellite imagery, for example, Sentinel 2 aided by cutting-edge algorithms can improve the estimation of foliar biochemical ratios. This study recommends that future research should adopt new satellite technologies with recent development in machine learning algorithms for improved mapping of the C:N ratio in grasslands.

Keywords: Rangeland, Carbon and nitrogen ratio, Remote sensing

2.1 Introduction

Globally, grasslands are the second-largest carbon sinks (Latham et al., 2014), accounting for over 40% of the landmass (Bar-On et al., 2018). Grasslands contribute significantly to food security by providing fodder to animals, thus providing livelihoods and economic support for rural communities as well as an array of ecosystem services (Teixeira et al., 2018, Bardgett et al., 2021). These ecosystem services include; sequestration of carbon for climate change mitigation, control of soil erosion, and regulation of nutrient cycling (Yuchun et al., 2011, Zhao et al., 2020). The social and societal benefits of grasslands include open spaces for leisure and recreation, cultural practices, and landscape aesthetics (Williams, 2015, Cornelis and Hermy, 2004). Despite their value, grasslands are constantly being degraded at accelerating rates (Bardgett et al., 2021, Muller et al., 2021). The transformation and degradation of grasslands can be attributed to a range of drivers that include climatic variability, invasive plant species, injudicious land use and management, and ecosystem fragility (Tiscornia et al., 2019, Li et al., 2022b). The degradation of grasslands leads to a reduction in forage quality and quantity at varying spatial extents (Hooper et al., 2012, Li et al., 2017), thereby adversely affecting livestock production and food security, especially within rangelands. Also, literature shows that foliar nutrient status/quality in rangelands is regulated by environmental conditions such as changes in temperature, precipitation, and soil nutrients, causing spatial variation in rangelands (Getabalew and Alemneh, 2019, Ghorbani et al., 2020). Therefore, a good understanding of rangeland properties is fundamental to developing robust analytical frameworks that can be used to obtain insightful information on their conditions and inform various strategic and operational decisions. Hence, rangeland managers must monitor grassland health/nutrient utilization to understand their effect on grassland productivity and quality.

Foliar biochemicals/nutrients play a major role in forage health and quantity. Foliar nutrients are an important variable in determining plant physiological status because they are linked to biomass productivity and vegetation health (Mokgakane, 2021). Foliar nutrients including nitrogen (N) and carbon (C) are important indicators of the quality and quantity of grasslands. Foliar N is important to vegetation because it constitutes amino acids, an important building block of proteins, as well as nucleic acids, chlorophyll, and other cellular components (Mu and Chen, 2021). In plants, the amount of nitrogen determines their growth, vigour, developmental stage, and functional role (Leghari et al., 2016, Band et al., 2022). Studies such as Yang et al. (2022) and Mu and Chen (2021) have highlighted that plants utilize and require N more than other nutrients. This is largely reflected in the large amount of N used during photosynthesis, especially Rubisco and molecules responsible for harnessing light energy (Nunes-Nesi et al., 2010, Evans and Clarke, 2019). The quantity of N invested enables the conversion of carbon dioxide, water, and inorganic nitrogen to make sugars, organic acids, and amino acids, which are essential for biomass production (Nunes-Nesi et al., 2010). Therefore, the availability of N determines both photosynthetic capacity and plant production (Nasar et al., 2021). In addition, the bond between C and N pathways is essential to the growth and development of plants. This is because photosynthesis requires a large amount of N, so, for optimal CO_2 absorption through photosynthesis and consequently biomass production, enough N supply is required (Mengesha, 2021). In summary, the amount and distribution of N is a key component of the carbon cycle and is a valuable indicator of plants' metabolism and development. According to Kocheva et al. (2020), the concentration of leaf N is related to plant photosynthetic capability, plant primary production, respiration, and the productivity and sequestration of C (Tang et al., 2018b). The ecosystem's C storage is limited due to N availability, affecting amongst others litter decomposition, soil organic carbon, and the allocation of C to various plant organs.

Grassland nutrients are affected by abiotic and biotic factors, including topography, temperature, precipitation, organic matter, and grazing (Zhang et al., 2021, Ravhuhali et al., 2021, Mokgakane, 2021). Changes in the C and N levels in grasslands over time, often lead to variations in the carbon-nitrogen (C:N) ratio (Onandia et al., 2019), thereby affecting the nutrient cycling and biomass in rangelands**.** The C:N ratio is critical in plant functioning and growth, and is widely adopted within both the field of ecosystem evolution and global climate change studies (He et al., 2006a). It is a measure of the efficiency with which nutrients are utilized by plants and influences the redistribution of biomass from root to shoot (Chen and Chen, 2021). Also, it promotes the accumulation of soil organic carbon, regulation of litter decomposition in plants, photosynthesis, net primary production, and to an extent indicates the growth rate of plants (Grechi et al., 2007, Zhang et al., 2020). Within rangelands, grazing animals require vegetation with high protein and a low C:N ratio <36 (< 36g of carbon for each 1g of nitrogen) (Beeri et al., 2007). This information is useful in rangeland management to determine when pasture cannot meet the minimum animal maintenance requirements. Despite grasslands' economic importance and their role in C and N cycling, there is a lack of spatially explicit data on grassland biophysical and biochemical properties. Therefore, to adequately monitor nutrient dynamics and productivity, a better understanding of the C:N ratio fluctuations in rangelands is needed (Liu et al., 2021b). However, few studies has been undertaken to synthesize the available literature on the importance of the C:N ratio within rangelands. This will be beneficial to decision-makers in rangeland management.

The traditional methods used in the determination of foliar N and C are based on plant measurements, and laboratory analysis (Sáez-Plaza et al., 2013, Catchpole and Wheeler, 1992). The estimation of foliar nitrogen has been done through laboratory techniques using the Kjeldahl digestion technique (Sáez-Plaza et al., 2013), and the Duma's combustion methods (Simonne et al., 1997). However, these methods are laborious, require long processing time, are costly, spatially restricted and chemical reagents used during analysis can destroy the samples (Muñoz-Huerta et al., 2013). Carbon has been estimated based on the biomass information derived through the direct/destructive method. The direct (plant-based) methods for estimating grassland above-ground biomass (AGB)/carbon stocks are based on plots and allometric equations from *in situ* measurements (Catchpole and Wheeler, 1992). The direct method involves clipping and weighing grass samples in the field for further laboratory analyses (Schaefer, 2015). While this approach is regarded to be accurate, it is not ideal for repeated measurements, time-consuming, laborious, and expensive (Prado Osco et al., 2019). Furthermore, leaf sampling and analysis are susceptible to human error, leading to inconsistencies and bias that may result in compromised data interpretation and significance (Singh et al., 2022). The direct estimation of foliar carbon and nitrogen individually may result in a C:N ratio that is susceptible to error, due to the inconsistent orders in the magnitude of C and N (Gao et al., 2020a). Thus, assessing the foliar C:N ratio directly with high-resolution sensors, may aid in reducing these errors. This is due to the high spectral and spatial resolutions that enable discrimination and mapping of features with relatively similar properties, with associated minimized errors (Reddy, 2021, Gao et al., 2020a).

Remote sensing offers a better alternative to understanding the estimation of rangeland foliar nutrient ratios in an ecosystem at several spatial and temporal resolutions (Ramoelo et al., 2012b, Shen et al., 2020). Remotely sensed data offers a timely, economical, and efficient approach to monitoring rangelands' foliar biochemicals for assessment and management (Ramoelo et al., 2012b, Lu et al., 2020). In addition, present advancements in sensor technology have enhanced the estimation and detection of changes in grassland health and biomass (Zhao et al., 2021, Schucknecht et al., 2021). In addition, remotely sensed data can be integrated with ancillary data, augmenting data-based decision-making in rangeland management.

Despite this knowledge, very few studies have utilized remote sensing to map the C:N ratio in grasslands. As a result, a review of techniques used within grasslands is therefore required along with areas and gaps that need further research. This is necessary to scientifically identify the priorities and challenges for future research in the application of remotely sensed data in rangeland studies. Previous reviews have majorly focused on the remote sensing of either foliar carbon or nitrogen in forests, crops, and rangelands. For instance, Xiao et al. (2019) reviewed the developments in remote sensing platforms and sensors of the carbon cycle over 50 years (1970 to 2019), while Naicker et al. (2019) quantitatively reviewed foliar nitrogen using remote sensing. In a related study, Wei and He (2020) conducted a global systematic review of the foliar C:N ratio in urban trees. Generally, there has been little research on the adoption of remote sensing techniques in quantifying the foliar C:N ratio, which is important in rangeland management. As such, this study examined remote sensing's opportunities to estimate foliar C:N ratios in rangelands, as well as its challenges and prospects. Such knowledge is important due to recent advancements in remote sensing technology. For example, recent advancements in broadband multispectral sensors (Sentinel 2 and Landsat8/9) with improved spectral and spatio-temporal resolutions provide new options to estimate foliar biochemical ratios in grasslands. Hence, this study provides a synopsis of remote sensing techniques to determine the foliar C:N ratio in grasslands, and their associated challenges, opportunities, and prospects. Our study will focus on (1) the remote sensing of foliar C:N ratio (2) analyze the various statistical and empirical methods used in the estimation of foliar C:N ratio, and (3) highlight the challenges and future research necessary to estimate foliar C:N ratio.

2.2 Remote sensing of foliar carbon to nitrogen ratio

The earliest effort to demonstrate the relationship between carbon and nitrogen in vegetation was by Blackman (1919), using laboratory-based techniques. Blackman (1919) developed the Blackman's concept, which reports an increase in carbon levels during catalytic activity in plants. During plant growth, the carbon-nitrogen interaction model can be developed using equation (1) below.

$$DM = DM0e^{CN1*N} \tag{1}$$

where DM is the final dry weight of the plant at a particular time, nitrogen (N)% is the amount of nitrogen stored in the plant at a particular time, DM_0 is the initial dry weight, and CNI is the carbon-nitrogen index, which is the value for ΔDM/ΔN/DM at a particular given period.

Blackman (1919), found that the productivity of plants is determined by their carbon and nitrogen content, since plants' nitrogen content and their photosynthetic rates are closely related. Increasing photosynthesis results in high nitrogen uptake by roots through enhanced water flow and root activity because carbohydrates are distributed widely throughout the roots. Therefore, it is presumed that there is a mutual regulation between carbon and nitrogen in plants.

As a result of this relationship, scientists have explored the relationship between C and N in plants using field and laboratory techniques (Tanaka and Osaki, 1983, Shinano et al., 1991, Osaki et al., 1992, Melillo et al., 1989, Corbesier et al., 2002). Although these approaches are accurate, they are expensive, laborious, and not practical at regional scales or remote areas. Therefore, as aforementioned, remote sensing is a cheaper and more spatially oriented alternative in the mapping and monitoring of foliar C:N ratio in plants due to its repetitive acquisition of spectral information at both local and regional scales. A selected number of researchers have demonstrated the capability of optical remote sensing data with machine learning algorithms and the radiative transfer method to detect the C:N ratio in plants (Xu et al., 2018, Gao et al., 2020a, Féret et al., 2021, Wei and He, 2020). However, remote sensing applications in C:N ratio estimation at a large scale and in heterogeneous environments is limited (Gao et al., 2020a). Therefore, we explore the utility of remote sensing technology in C:N ratio estimation at various scales through an extensive review of the literature.

2.2.1 Hyperspectral remote sensing of foliar C:N ratio

Hyperspectral sensors, also known as imaging spectroscopy contain many narrow continuous bands through the visible, near-infrared, and short wave infrared regions of the electromagnetic spectrum (Berger et al., 2020b, Mutanga et al., 2003). Hyperspectral data can better distinguish and estimate subtle biochemical and biophysical properties in grasslands (Marabel and Alvarez-Taboada, 2013, Yu et al., 2020a, Schweiger et al., 2015) compared to traditional broadband (> 100 nm) multispectral data (Kumar et al., 2001), due to their several bands. Hyperspectral data are primarily collected by handheld spectrometers or airborne sensors. Since the invention of the airborne visible/infrared imaging spectrometer (AVIRIS) in 1987, hyperspectral sensors have been utilized in vegetation studies. For example, using AVIRIS data, (Kupiec and Curran, 1995) examined whether the canopy effect (structure, biomass, LAI, and shadow) altered foliar nutrient concentrations in the canopy reflectance spectral region.

The study demonstrated that at wavelengths beyond 1400nm, the canopy influences leaf reflectance, while near-infrared leaf properties remain unchanged.

Several studies (Xu et al., 2018, Gao et al., 2020a, Chen et al., 2019, Beeri et al., 2007, Lihong et al., 2006), have explored the capabilities of hyperspectral data in determining the foliar C: N ratio in vegetation. According to Xu et al. (2018), the monitoring of foliar C:N ratio using remotely sensed data, especially with hyperspectral imagery is still at the exploration stage. Using two sets of field data with different nitrogen levels and rice cultivars, Zhou et al. (2009) suggested that band 672nm could monitor foliar C:N ratio in rice using canopy hyperspectral parameters. Also, Lihong et al. (2006) established that NDVI derived from the integration of two spectral bands at 710nm and 1650nm from rice canopy reflectance spectra could map leaf C:N ratio. Building on this, Xu et al. (2018) investigated the use of spectral response curve from canopy hyperspectral reflectance data with the Branch and Bound algorithm to retrieve foliar C:N ratio in wheat and barley. Their results indicated that the change in the C:N ratio could be evaluated with an accuracy of R^2 of 0.63, 0.68. 0.65 for wheat, barley, and both species combined respectively, using the best slope feature. Another attempt to map the C:N ratio was by Gao et al. (2020a) in the alpine grasslands, China, using field hyperspectral data, and random forest algorithm. They found the red and red edge bands to be useful in estimating C:N ratio using the random forest algorithm.

However, despite the accuracy obtained from these sensors, data acquisitions are often hampered by plants' canopy characteristics (leaf area index and canopy cover) (Jiang et al., 2021). Gara et al. (2018) demonstrated that variation in light availability and leaf shading affects the biochemical and morphological characteristics including chlorophyll, nitrogen, dry weight, and photosynthesis due to different canopy structures. These often result in different spectral values between the top and the bottom surface of the same leaf. For instance, Chen et al. (2019) quantified the leaf carbon, nitrogen, and C:N ratio in soya beans under different light conditions using hyperspectral reflectance. The results showed that leaf nitrogen increased while carbon decreased with an increase in shading. They concluded that the continuous wavelet transformation model had the lowest root mean square error (RMSE) of 1.9789, 0.6132, and 2.1587 for carbon, nitrogen, and C:N ratio, respectively. However, whereas these studies have demonstrated that light variation/shading influences the plant biochemical contents, there has been a lack of focus on quantifying the effect of different shading levels/light variations on C:N ratio in plants, especially within rangelands.

Some studies (Gao et al., 2020a, Chen et al., 2019, Xu et al., 2018) indicate that near-infrared and red edge bands can map C:N ratio in vegetation. These studies have demonstrated the effectiveness and capability of hyperspectral sensors to retrieve foliar C:N ratio in grasslands. Results from the aforementioned studies indicate the possibility of estimating rangelands' C:N ratio using hyperspectral sensors' spectral properties. In summary, hyperspectral data can capture the subtle variation in vegetation due to hundreds of bands ranging from 350nm to 2500nm, which is critical for plant monitoring. However, hyperspectral data is costly, especially for regional mapping, and not readily available (Tong et al., 2013, Feifei et al., 2020). Furthermore, the absorption features of most foliar biochemicals, such as cellulose, lignin, nitrogen, and starch, are affected by water in fresh leaves. Due to this challenge (Gao and Goetz, 1994) developed the water removal approach to deal with the masking effect of water from fresh leaves. Following up on the study, Schlerf et al. (2010) modified the technique.

2.2.2 Multispectral sensors in estimating foliar C:N ratio

The conventional multispectral sensors including MODIS, SPOT, ASTER, and Landsat series with medium to coarse spatial resolution have been used to estimate plant nutrients. They are usually limited to the regional mapping of vegetation's physical and chemical properties because of their limited spectral channels and discontinuous bands (Yin et al., 2015, Anderson et al., 1993). The remote sensing fraternity recently witnessed the advancement in technology of freely available optical sensors with improved spectral, radiometric, and spatial resolutions such as Landsat8/9, and Sentinel 2 suitable for mapping grasslands' morphological and biochemical properties (Soltanian et al., 2021, Pang et al., 2022, Adagbasa and Mukwada, 2022). Therefore, it is necessary to adopt these freely available multispectral sensors to map foliar nutrient ratios such as C:N ratio. However, Rahman et al. (2020) noted that there is limited application in assessing leaf C:N ratio using freely available sensors, including Landsat 8 and Sentinel 2. Rahman et al. (2020) utilized Landsat 8 and Landsat TM5 bands, texture metrics, and indices to map the spatiotemporal variation of C:N ratio of senescent leaves in a reserved forest using machine learning techniques. Their study reported that bands sensitive to moisture and temperature (thermal and short wave infrared bands) are the top predictors in modelling the foliar C:N ratio using freely available Landsat TM data. The effectiveness of Landsat 8 can be attributed to the push broom scanner with a high signal to noise ratio that predicts foliar properties more accurately compared to its predecessors. Despite the noticeable success of the study by Rahman et al. (2020), there is a gap in the use of the Landsat series to predict C:N ratio, particularly in rangelands. So, future research must examine the strength of recent sensors such as Landsat 8/9 with improved spectral and spatial properties in estimating C:N ratio in grasslands. Notwithstanding, in recent times, there has been a shift toward advanced, cheaper, or freely available multispectral sensors equipped with red edge bands suitable for determining foliar nutrients.

Furthermore, advanced and readily available multispectral sensors, including Sentinel-2, have additional red edge spectral regions, thus comparable to commercial sensor systems (WorldView-3 and RapidEye) with a high spatial resolution (Omer et al., 2017, Westergaard-Nielsen et al., 2021, Sagan et al., 2021). The freely available Sentinel 2 is equipped with 13 absorption wavebands in the visible to shortwave infrared, with additional red edge bands (705, and 740, 783 nm) (Adagbasa and Mukwada, 2022). Mutanga and Skidmore (2007), Clevers and Gitelson (2012) and Koley and Chockalingam (2022) illustrated that the red edge bands are sensitive to the vegetation properties (nitrogen, biomass, and canopy structure). Despite these studies producing reasonable results, few studies have used advanced multispectral sensors to estimate C:N ratios. For example, Westergaard-Nielsen et al. (2021) quantified the spatiotemporal variations in Artic tundra leaf C:N ratio based on the new Sentinel 2 derived index. The results showed that the normalized reflectance index (NRI_{1610}) derived from the shortwave infrared and red edge bands, estimated the C:N ratio with an accuracy of $R^2 = 0.81$. From the aforementioned study, the use of advanced and open-source multispectral sensors based on the red-edge spectral bands have the potential to determine the C:N ratio of rangelands. This will augment the available understanding of estimating the rangeland biochemical ratio in future research.

In addition, the integration of sensors in the estimation of nitrogen and biomass may be beneficial in providing additional information for complex applications in heterogeneous areas with varying structural properties. This is because of the unique spatial and spectral resolution in each sensor. However, there are no available studies on the benefits of sensor integration in estimating foliar nutrient ratios such as C:N ratio, especially in rangelands. In recent times, the fusion of optical, LIDAR, and radar data has improved model accuracy for biomass and quality estimation of highly heterogeneous grasslands. For example, Grüner et al. (2020) combined terrestrial laser scanning (TLS) with unmanned aerial vehicle-based multispectral (MS) data to estimate biomass and nitrogen fixation in different grass-legume mixtures. The fusion of TLS and MS yielded the best accuracy with a relative root mean squared error of prediction (rRMSEP) of 14%, whilst MS (rRMSEP of 18%) and TLS (rRMSEP of 21%) for nitrogen fixation in the grass-legume mixture. The study highlights the importance of point cloud data and optical sensors in improving model prediction in vegetation studies, which can be applied in the estimation of foliar C:N ratio. Therefore, this integration of sensors may be beneficial in improving the prediction of the C:N ratio in rangelands.

Presently, cost-effective Unmanned Ariel Vehicles (UAVs) are developing technologies in the estimation of grasslands parameters. In addition to providing high-spatial-resolution imagery, UAVs are also less subject to cloud and haze interference, making them suitable for measuring grassland aboveground biomass and biochemicals (Franceschini et al., 2022, Schucknecht et al., 2022). For instance, Schucknecht et al. (2022) evaluated the effectiveness of UAV-borne multispectral data for determining dry biomass and nitrogen (N) concentration of pre-Alpine grasslands. The authors produced a relative root mean square error (average cross-validated) $rRMSE_{cv}$ of 12.6 % for dry biomass and $rRMSE_{cv}$ of 14.2 % for N model using the raw reflectance and vegetation indices. It is therefore hypothesized that the robustness of UAVs might improve the mapping of foliar biochemical ratios in grasslands. Future research should test the strength of UAVs in monitoring grasslands' C:N ratio.

2.3 Influential spectral variables in estimating C:N ratio

The estimation of foliar nutrients depends on absorption features in the near-infrared and shortwave infrared region (Knox et al., 2012). Studies such as Curran et al. (2001), and (Mutanga and Skidmore, 2004a) have identified absorption features related to biochemical nutrients in vegetation. For instance, the absorption bands (1020nm, 1510nm, 1730nm, 1980nm, 2060nm, 2130nm, 2180nm, 2240nm, 2300nm) have been used to quantify nitrogen, chlorophyll, and protein of foliar biochemical (Curran, 1989, Naicker et al., 2019, Gao et al., 2020a, Ramoelo et al., 2013). Similarly, some known absorption bands (910 nm, 930 nm, 1020 nm; 1040 nm, 1120 nm, 1510 nm, 1690 nm, 1730 nm, 1780 nm, 1980 nm, 2000 nm, 2060 nm, 2100 nm, 2130 nm, 2180 nm, 2240 nm, 2270 nm, 2280 nm, and 2300 nm) of cellulose, starch, lignin, and sugar absorbing in the SWIR region have been used in the detection of carbon compounds in vegetation (Thulin et al., 2014, Pullanagari et al., 2012, Gao et al., 2020a), since specific wavebands for carbon have not been identified.

Also, parameters in the red and red edge region (slope, position, amplitude, and index) have produced promising results in predicting grasslands N, chlorophyll, cellulose, lignin, carbohydrates, and biomass content (Mutanga and Skidmore, 2007, Gao et al., 2020a, Guerini

Filho et al., 2020). For example, Durante et al. (2014) identified absorption bands in the red, red-edge, and SWIR regions that could predict the C:N ratio in grass using leaf spectral reflectance. In barley and wheat leaves, Xu et al. (2018) noted that based on the spectral slope features, bands in the red edge performed better at predicting the C:N ratios. In another study, Gao et al. (2020a) tested the strength of hyperspectral data bands to determine the C:N ratio in grasslands using the random forest and support vector machine algorithms. According to their findings, the red, red edge, and SWIR (1950-2350 nm) bands performed well in predicting foliar C:N ratios, with coefficients of determination of validation (V-R^2) ranging from 0.70 to 0.80.

The empirical-based model of estimating foliar biochemicals involves the use of vegetation indices, absorption features, full-spectrum, and integrated modelling. The estimation of foliar biochemicals has been extensively done using vegetation indices, which combine different spectral reflectance bands. Traditional broadband indices (Normalized Difference Vegetation Index, Modified Simple Ratio, and Soil Adjusted Vegetation Index) have been explored to quantify the biochemical content of plants (Rahman et al., 2020, Farella et al., 2022). In particular, Gao et al. (2020a), Rahman et al. (2020), and Lihong et al. (2006) utilized spectral indices from traditional broadband indices (NDVI, SAVI) in the prediction of the C:N ratio. Lihong et al. (2006) reported that NDVI with bands 710nm and 1650nm could determine the C:N ratio of rice at the late growth stage. Also, Rahman et al. (2020) ranked Landsat TM5 and Landsat 8 vegetation indices among the top 10 predictors in mapping the spatiotemporal variations of C:N ratio of senescent leaves in a reserved forest, Bangladesh. However, these conventional broadband indices suffer from saturation in dense vegetation and are insensitive to subtle changes in foliar biochemicals (Mutanga and Skidmore, 2004b).

In contrast, several researchers have concluded that red-edge indices of hyperspectral data and advanced multispectral data can reduce the saturation effects of traditional broadband indices (Imran et al., 2020, Liu et al., 2022a, Ramoelo et al., 2015c). In leaf, the red-edge region is the rapid rise in reflectance between 680nm and 780nm (Mutanga and Skidmore, 2007). In addition, the red-edge bands from advanced broadband sensors such as Sentinel 2, World view, and Rapid Eye have been reported to improve the prediction accuracy of foliar nutrients (Vasudeva et al., 2021, Ramoelo et al., 2012b, Imran et al., 2020). For instance, Vasudeva et al. (2021) mapped the spatial distribution of forest nitrogen and carbon in India using Sentinel 2 band and vegetation indices and machine learning algorithms. Their investigation showed that the random forest algorithm could accurately predict foliar nitrogen and carbon with an

R^2 of 0.85 and R^2 of 0.86, and the most important indices in predicting C and N had red edge bands. The success of Sentinel 2 in estimating foliar nutrients (carbon and nitrogen) is due to the strategically positioned red edge bands, the 10 to 60m spatial resolution, and the high temporal resolution (5 days) which is adequate for monitoring and management of rangelands (Imran et al., 2020). Although the red edge in Sentinel 2 MSI has been used extensively in estimating nitrogen in vegetation, the effectiveness of Sentinel 2 data to estimate foliar carbon is at an exploratory stage, and a clear understanding of the spectral properties that can estimate carbon in plants is necessary. Furthermore, the strength of new red edge indices (red edge normalized difference vegetation indices, Inverted red-edge chlorophyll index, and Sentinel 2 red edge position index) have been documented to have high predictions in estimating foliar nutrients (Liu et al., 2022a, Koley and Chockalingam, 2022). There is a need to test these new red edge indices in mapping the C:N in rangelands, as no such literature exist. Hence, it can be concluded that the spectral properties of plants either from field measurements, UAVs, airborne sensors, or satellite imagery influence the effectiveness of vegetation indices based on foliar ratios such as C:N ratio. However, Pacheco-Labrador et al. (2014), also noted that vegetation indices could be affected by differences in plant type, season, and the impact of the range in canopy foliar concentration.

In summary, the literature notes that absorption features sensitive to C:N ratio dominates the near-infrared, SWIR, red, and red edge regions (Gao et al., 2020a, Beeri et al., 2007, Rahman et al., 2020). Also, spectral transformation techniques (continuum removal, derivatives) improve the accuracy in predicting C:N ratio in grasslands (Gao et al., 2020a). A large number of the studies on the estimation of C:N ratio is largely dominated by hyperspectral data using machine learning algorithm in forests and croplands. This is due to the ability of hyperspectral sensors to detect minute details in vegetation. Also, there is limited research in the application of freely available, advanced multispectral sensors (Sentinel 2 and Landsat 8) in predicting foliar biochemical ratios in rangeland, especially the C:N ratio. Furthermore, there is a gap in the application of modern remote sensing technology such as UAVs to predict the C:N ratio in grasslands. The use of UAVs holds better prospects in estimating rangeland C:N ratio due to its low cost, flexibility in data acquisition and sensor integration, and wide field of view.

2.4 Regression and machine learning algorithms utilized in estimating C:N ratio

The challenges of analyzing remotely sensed data include, the processing of a large amount of data, varying spatial-temporal and spectral properties, and a wide range of proximate bands.

Therefore, techniques that can analyze, integrate and help make the best-informed decisions from the huge amount of datasets are necessary. Several studies have adopted techniques such as parametric and non-parametric (linear regression, non-linear regression) in mapping foliar nutrients using remotely sensed data (Prado Osco et al., 2019, Maimaitijiang et al., 2020b, Das et al., 2020). In particular, the non-parametric models (linear and nonlinear machine learning algorithms) compute coefficients to reduce the error associated with variables extracted. As a consequence, the model development is simplified, since no explicit parametrization is necessary; however, it may require a higher level of expertise to understand and execute these models (Verrelst et al., 2019).

Multivariate linear regression methods such as the stepwise multiple linear regression (SMLR), partial least square regression (PLSR), and support vector machine (SVM) have been used as predictive models to estimate plant nutrients (Berger et al., 2020b, Hou et al., 2018). Stepwise multiple linear regression (SMLR) was commonly utilized in earlier studies for the extraction of nutrient content from spectral data (Kokaly, 2001, Mutanga et al., 2004b). Peng et al. (2020) used stepwise linear regression and hyperspectral data to map leaf nutritional status in degraded plants with an $R^2 = 0.5–0.8$, $p < 0.05$. However, these methods (i.e. SMLR) assume that data is normally distributed, and so may suffer from overfitting and multi-collinearity, especially in hyperspectral datasets (Huang et al., 2004). In contrast, PLSR produces robust and better models due to its ability to reduce spectral data into fewer orthogonal variables. However, the relationship between plant variables and spectra data is non-linear and complex, so PLSR might not be ideal for hyperspectral analysis. For example, to estimate leaf nitrogen content, Yi et al. (2014) compared SMLR to PLSR and nonlinear machine learning regression algorithms. The nonlinear regression outperformed the SMLR and PLSR due to their flexibility.

Non-linear non-parametric regression, also referred to as machine learning algorithms (ML) have the advantage of capturing nonlinearity among image features without relying on the underlying distribution of data. Machine learning algorithms (i.e Random forest (RF), and Stochastic Gradient Boosting (SGB)) have the potential to rapidly generate adaptive and robust relationships, once trained. (Chlingaryan et al., 2018, Barzin et al., 2021). These algorithms have been used to estimate plant biomass and nutrients. Machine learning algorithms can handle the nonlinearity between vegetation parameters (biochemical and biophysical properties) and the reflected radiance (Chlingaryan et al., 2018)**.** They may therefore be more appropriate in vegetation studies. Some studies (Shi et al., 2021, Gao et al., 2020a, Xiao et al., 2019) have illustrated that non-linear regressions (stepwise multiple linear regression), and kernel-based extreme learning machine regression (cubist and extreme learning regression) are superior to linear regressions in quantitative models. This is because they are flexible, and can handle highly correlated predictors with efficiency in picking the key predictors amongst several predictors (Pullanagari et al., 2016, Prado Osco et al., 2019).

For example, Pullanagari et al. (2016) utilized airborne hyperspectral data with non-linear machine algorithms (RF, SVM) and linear PLSR in predicting several foliar nutrients in a mixed pasture. Their study indicated that RF and SVR outperformed PLSR in estimating different foliar nutrients. Similarly, Maimaitijiang et al. (2020a) and Gao et al. (2020a) successfully mapped the plant C:N ratio with RF. The random forest algorithm has an excellent ability to overcome the issues of multi-collinearity and to investigate the internal relationships of specific foliar biochemical and biophysical properties with multiple spectral data (Fernández-Habas et al., 2022, Otgonbayar et al., 2019). The RF comprises of different decision trees that are widely applied in varying classification and regression problems (Maimaitijiang et al., 2020a). These machine learning models have the advantage of easily handling several predictor variables derived from ancillary and remotely sensed data related to foliar nutrients and carbon stocks (Xiao et al., 2019). Using the RF approach to predict the C: N ratio in grasslands from *in situ* hyperspectral data has also produced promising results Gao et al. (2020a). Shi et al. (2021) concluded that the random forest not only has the advantage over the support vector machine but also exhibits model simplicity and circumvents overfitting.

However, Artificial Neural Networks (ANNs) have multiple variants with various topological structures (Chen et al., 2013, Liu et al., 2018), making them flexible with the ability to generalize and perform efficiently with the appropriate setting of model parameters. ANN comprises of multiple hidden and output layers of interconnected groups of nodes (Torkashvand et al., 2020). Each neuron is trained to produce outputs based on some activation function, training algorithm, initial weight, and biases (Wang et al., 2009). However, the ANN suffers from overfitting, which may likely influence model prediction. Different studies have used algorithms such as the ‘Save best’ and ‘early stopping’ strategies to prevent overfitting in the ANN (Srivastava et al., 2014).

Another attempt to estimate C:N ratio using the machine learning algorithm was by Rahman et al. (2020) in the mangrove ecosystem between Bangladesh and India using SGB, RF, SVM, and PLSR. The SGB, RF, and SVM performed better than the PLSR. They concluded that the C:N ratio and predictor variables are non-linear related in the reserve forest, hence the weak performance of the PLSR modelling technique which is linear based (Sun et al., 2019b). The aforementioned studies indicate that non-linear models have better performance in predicting C:N ratio in plants. Therefore, studies on C:N ratio in rangelands should focus on the improved accuracy of non-linear models as there is a paucity of data in this regard.

In recent times, Das et al. (2020), and Mahajan et al. (2021) concluded that models which integrate linear with non-linear algorithms can improve model accuracy, better than individual multivariate techniques in the estimation of foliar nutrients (Das et al., 2020, Mahajan et al., 2021). According to Das et al. (2020), the robustness of these integration models lie in their ability to reduce multi-collinearity problems, and increase processing speed, while retaining most of the information in the original dataset. Also, the use of principal components, latent variables, and selection of variables through variable importance as input for further machine learning modelling makes this method possible (Mouazen et al., 2010). In addition to reducing collinearity, data dimensionality, and speeding up computation, these approaches preserve most of the original dataset's information (Yang and Ge, 2020). The integration of linear and non-linear regression analysis has been demonstrated in a few studies, but very limited information is available on this aspect in grasslands, specifically mapping foliar C:N ratio in rangelands. The combination of these models is important to evaluate whether the integration of models will provide robust results in comparison with individual ones in estimating foliar C:N ratio in grasslands.

Nevertheless, machine learning algorithms are limited as they are designed to suit certain types of data. Consequently, a method that works for one task may not be as effective for another. In addition, the original reflectance spectra require several pre-processing methods (first derivative, continuum-removal) to obtain more accurate predictions when using the multivariate regression methods (Gao et al., 2020a, Ramoelo et al., 2013). It is therefore possible to achieve different predictive outcomes by using different spectral pre-processing techniques. Hence, it is challenging to balance between model complexity and accuracy when choosing pre-processing and multivariate regression methods.

Recently, the use of deep learning (DL) algorithms: convolutional neural networks and Stacked Sparse Autoencoder networks that present data hierarchically has attracted broad attention in vegetation studies (Maimaitijiang et al., 2020b, Ahsan et al., 2021). The DL algorithm has been successfully used to map foliar biophysical and biochemical properties (Azimi et al., 2021, Buxbaum et al., 2022). DL is a unique ML algorithm that utilizes several layers of non-linear information to model complex relations among data. As a result of its ability to rely primarily on data for image recognition, deep learning is considered to be a powerful tool (Buxbaum et al., 2022). Furthermore, Pullanagari et al. (2021), Odebiri et al. (2021) and Yuan et al. (2020) have reported the superiority of DL over ML and geostatistical methods. For example, using a large field spectroscopy database, Pullanagari et al. (2021) compared the accuracy of one-dimensional convolutional neural network (1D-CNN) with PLSR and gaussian process regression (GPR) in estimating canopy nitrogen in grassland. The results showed that in comparison to PLSR (0.31) and GPR (0.16), prediction derived using 1D-CNN achieved greater accuracy with <0.12 mean standard deviation. Therefore, due to its optimal accuracy and better performance, it is necessary to evaluate the utility of DL in mapping C:N ratio in rangelands, as there is no available literature. Despite the optimal performance and higher accuracies of emerging machine learning algorithms in the estimation of foliar nutrients, no standard method has been identified to be optimal for mapping foliar nutrients using different remotely sensed data. Hence, future studies need to investigate the use of more robust algorithms to estimate C:N ratio in rangelands.

2.5 Radiative transfer model in the estimation foliar C:N ratio

Radiative Transfer Models (RTMs) are physical models that depict how solar radiation interacts with vegetation based on optics laws (Myneni et al., 1992). These RTM models include PROSPECT (Jacquemoud and Baret, 1990), PROSAIL (an integration of PROSPECT which is a leaf level model, and SAIL which is a canopy level model), and LIBERTY (Dawson et al., 1998). Earlier studies on the reflectance of leaf modeling were established on the "Kubelka-Munk" theory of radiative transfer (Allen and Richardson, 1968). Jacquemoud and Baret (1990), derived the PROSPECT model from Allen et al. (1969) generalized plate model, which describes leaf optical properties from 400nm to 2500nm. The RTMs have been widely used in predicting foliar biochemical such as dry matter, water, and chlorophyll (Darvishzadeh et al., 2008, Feret et al., 2008, Sun et al., 2019a), with limited studies on cellulose, lignin, protein of plants from remotely sensed data (Wang et al., 2015b). Some researchers have utilized the PROSPECT model to derive foliar biochemical properties including nitrogen, protein, cellulose, and lignin (Wang et al., 2015b, Féret et al., 2021, Wang et al., 2021b). According to Jacquemoud et al. (1996), the retrieval of foliar nitrogen from fresh leaves was considered impossible using RTMs methods. However, Wang et al. (2015b) estimated leaf protein from the spectra of fresh leaves, using the PROSPECT 5 leaf model, which combines the effects of foliar protein, cellulose, and lignin.

A limited number of studies, e.g Féret et al. (2021) have directly utilized the radiative transfer model in estimating foliar C:N. According to Féret et al. (2021), until recently, the shortcomings of physically-based leaf radiative models included the inability to decompose spectral components correctly and estimate nitrogen-based proteins and other carbon contents of fresh and dried leaves based on optical properties. Building on this shortcoming, they developed the PROSPECT PRO model, the most recent version of the PROSPECT model (Jacquemoud et al., 1996), that separates leaf dry mass per unit leaf area (LMA) into nitrogen-based constituents (protein) and carbon-based constituents (*CBC*). For instance, Berger et al. (2020a), noted that the PROSPECT PRO model was calibrated using fresh and dry leaves and it is based on the principle that the nitrogen constituents and *CBC* (cellulose, lignin, hemicellulose, and starch) are a complementary part of the total leaf LMA. Fresh and dry leaves were used to calibrate PROSPECT PRO, and in both types of leaves, the model was validated with similar estimates of protein content. In a similar study, Féret et al. (2021) used the new PROSPECT PRO model to determine the nitrogen-based constituents of leaf protein and other carbon-based constituents using dry and fresh broadleaf and grass samples from the LOPEX dataset. They reported that the PROSPECT-PRO can determine the carbon-to-nitrogen ratio with R^2 of 0.87 for fresh leaves, and R^2 of 0.65 for dry leaves, based on the *CBC*-to-proteins ratio. The study concluded that optimal selection of spectral features improved the assessment of leaf constituents from fresh samples. As a result, the PROSPECT-PRO model appears to be well suited for the quantification of the C:N ratios, which may be relevant for vegetation studies in conjunction with data from current and upcoming satellite sensors.

The radiative transfer model offers the advantage of robustness and transferability to other regions because its analysis of vegetation properties is established on the physical laws and it is not dependent on the sensor, site, or season (Berger et al., 2018). However, it is seldom used due to model complexity and computational challenges (Lu and He, 2019) and may be unsuitable for real-time analysis. Consequently, in recent times, the integration of the RTM such as PROSAIL with machine learning algorithms known as the Hybrid model has been used to derive biochemical and biophysical properties for vegetation (Danner et al., 2021). Literature notes that this is a promising approach to retrieving biochemical and biophysical information from earth observation sensors, for example, Sentinel 2 and Landsat 8 (Rivera-Caicedo et al., 2017, Doktor et al., 2014, Verrelst et al., 2019). For instance, Danner et al. (2021) combined the PROSAIL model with several machine learning algorithms (RF, ANN, and gaussian processing regression(GP) to provide spatial information about foliar biophysical and biochemical properties (i.e chlorophyll level, leaf area index, leaf mass per area) with relative error scores less than 10%. Imaging spectroscopy can be processed more quickly (Verrelst et al., 2019) because the hybrid model combines the adaptability and computational efficiency of machine learning with the physical basis of the RTMs (Berger et al., 2020b).

These studies have demonstrated that recent advancements in the hybrid method have the potential to improve model accuracy in estimating plants' biophysical and biochemical properties, whereas the robustness of the hybrid method is documented in vegetation studies (Brown et al., 2019). In Africa, within a semi-arid landscape, Kganyago et al. (2020) noted low accuracies in the leaf area index with RMSE > 1 m^2 m^{-2}. Therefore, it is necessary to test the accuracy and reliability of hybrid models compared to RTM as a more viable option in estimating rangeland biochemical concentrations such as C:N ratio.

2.6 Factors affecting the spectral characteristics of foliar nutrients

The spectral absorption bands sensitive to foliar biochemical such as C and N dominate the short wave infrared (SWIR) and near-infrared (NIR) region (Curran, 1989, Ramoelo et al., 2011, Kokaly and Clark, 1999). In the SWIR, the absorption features for leaf biochemical concentration include cellulose, protein, starch, and lignin. Also, specific wavebands for C have not been identified, however, the SWIR has been reported to predict foliar C concentration (Gao et al., 2020a, Benseghir and Bachari, 2021). The estimation of foliar biochemicals from dried leaves, fresh leaves, and canopies using remotely sensed data is affected by several challenges. Amongst this is the absorption of water in the shortwave infrared which masks subtle foliar biochemical concentrations (Kokaly and Clark, 1999, Clevers, 1999). As such, the accuracy of estimating foliar C and N is strongly affected by the absorption of water in the NIR and SWIR region, which can disguise the absorption effect of other nutrients (Curran et al., 1992). Furthermore, Asner et al. (2000) and Cho and Skidmore (2006) noted that differences in leaf traits, soil background, with atmospheric effect complicate the estimation of foliar biochemicals in the field. Several techniques such as continuum removal method, derivative spectra, and log-transformed spectra have been introduced to enhance the identification of biochemical absorption features in addition to data redundancy (Mutanga and Skidmore, 2003, Kokaly, 2001). For example, Gao et al. (2020a) enhanced the detection of important bands that significantly quantify the C:N ratio in forage by using continuum-removed and first derivative spectra. This study deduced that the spectra transformation methods enhance the absorption and reflection values, eliminated noise, and increased the number of bands that can accurately predict forage C:N ratio. The absorption of foliar biochemicals such as cellulose, lignin, and starch in fresh leaves is weak and usually masked by water. Gao and Goetz (1994) successfully developed a non-linear technique that removes the effects of water absorption from fresh leaves. The method was improved by Schlerf et al. (2010) and used to model nitrogen levels in Norwegian spruce needles. In addition, Skidmore et al. (2010) reported that the use of remotely sensed data to determine foliar nutrients can be challenging due to the difficulty to separate the signal of biomass and foliar nutrients, especially N. This effect can be minimized at the peak of biomass, where there is high absorption in the red edge and scattering in the near-infrared region of grass spectra. During the peak of biomass, the interaction between biomass and vegetation indices such as NDVI asymptotically saturates at a certain biomass density (Thenkabail et al., 2000, Mutanga and Skidmore, 2004b). Due to the variation in grass biomass, the accuracy of estimating foliar N using vegetation indices can be compromised. Nevertheless, Mutanga and Skidmore (2004b) used narrow-band vegetation indices for biomass estimation in dense vegetation with high accuracy.

2.7 Challenges and opportunities in estimating foliar C:N ratio

A review of literature shows that hyperspectral sensors have been used extensively to predict foliar C:N ratio due to their ability to map spatial variation and identify highly discrete spectral features in vegetation that are ignored by broadband sensors (Clevers and Kooistra, 2011). Hyperspectral sensors can provide sufficient spectral information, however, they are costly, have small swath widths, and are not readily available in developing countries. The broad band multispectral sensors may not be appropriate in the estimation of C:N ratio, as a result of the limited number of absorption wavelengths in the SWIR region. Durante et al. (2014) and Gao et al. (2020a) demonstrated in different studies that bands sensitive to C:N ratio in vegetation are in the SWIR region. Advanced multispectral sensors (Rapid eye, Sentinel 2, and Worldview3) with an improved spatial and temporal resolution with specialized red edge bands have proved invaluable in vegetation studies (İleri and Koç, 2022, Sibanda et al., 2017b, Vasudeva et al., 2021). There is a paucity of information on the use of these sensors to predict C:N ratio, as the red and red edge region, may improve the accuracy of C:N ratio prediction in rangelands.

The use of unmanned aerial vehicles in estimating foliar biochemical ratios in rangelands remains largely unexplored. Unmanned aerial vehicles (UAV) have an edge over traditional field surveys due to their flexibility, small size, cost, and application in any chosen sites (Cerro et al., 2021). Future research on foliar biochemicals should focus on integrated technologies for multispectral sensors and UAVs in the monitoring of rangelands based on data quality (spatial image and resolution) and accessibility (technical expertise and affordability). According to Karunaratne et al. (2020), the fusion of the spatial and spectral data in sensors has gained increasing interest as a new method of estimating forage quality and quantity. This is due to its ability to overcome the saturation problems of soil background in low biomass, and saturation in dense vegetation (Mutanga and Skidmore, 2004a), as canopy reflectance is captured at the top surface.

Advances in algorithms, such as integration of linear and non-linear models, deep learning, and machine algorithms can further improve the accuracy and identify the optimal variables using variable importance in projection techniques to determine the C:N ratio in rangelands. This prompts the need for future research on rangelands to test the strength of advanced sensors with machine learning algorithms, non-parametric, and combined machine learning algorithms with non-parametric approaches in the estimation of foliar C:N ratio. Also, factors (i.e environmental and climatic) that influence the spatial variation of C:N ratio in rangelands remain unknown. Thus, future studies need to investigate the stoichiometric fluctuations of rangeland C:N ratio response to topo-climatic variables within the ecosystem.

The PROSPECT-PRO inversion model has provided a successful approach to estimating the C:N ratio using the *CBC*: proteins (Féret et al., 2021), but its use is still limited by several challenges. For instance, they reported that discrepancies in sample numbers might lead to errors and uncertainties in the calibration and validation datasets. To address this challenge, it is suggested that additional free datasets with accurate VNIR and SWIR spectral properties with commensurate detailed and reliable laboratory analysis of foliar biochemical composition are required. Furthermore, despite the shortcomings of chlorophyll-a +b contents as indicators for the estimation of nitrogen (Homolova et al., 2013), it has the advantage over protein due to its high signal at the VNIR (particularly red edge), enabling more accurate estimations even at canopy levels (Malenovský et al., 2013). It is therefore likely that a systematic and rational combination of chlorophyll monitoring with PROSPECT PRO would provide an enhanced assessment of the C:N ratio in vegetation, and periodic fluctuations by separating the *CBC* and protein contents. Hence, further studies should focus on the use of RTMs in the estimation of

C:N ratio in rangelands. The use of the PROSPECT-PRO model may prove invaluable in the estimation of C:N ratio in rangelands.

2.8 Conclusion

This review has provided an overview of remote sensing techniques utilized in the estimation of the C:N ratio in rangelands with associated challenges and opportunities. Grassland C:N ratios are indicators of nutrient utilization and limitation within rangelands, and they vary in different locations. Majority of the studies on foliar C:N ratio have mostly focused on forest and croplands, while less effort has been exerted on rangelands. Although the conventional methods have been reliable, remote sensing is a non-destructive, rapid, and cheaper means of estimating foliar nutrients in rangelands at a landscape scale. Remote sensing offers spatially explicit and periodic information on the available nutrients over regional and inaccessible areas. Also, most studies have used hyperspectral data in determining foliar C:N ratio. Despite the success of hyperspectral data in estimating foliar C:N ratio in plants, they are costly and not readily available, especially in resource-scarce and financially constrained countries in Africa. Further, this study reveals that the estimation of foliar C:N ratio in rangelands, using freely available high resolution multispectral, such as Sentinel 2 and Landsat 8 is still in infancy. The success of Sentinel 2 is attributed to the red-edge bands, therefore, more studies should test the red-edge bands in estimating C:N ratio, particularly in rangelands. In addition, literature shows that integrating remotely sensed data with ancillary data (topographic and climatic) can improve the accuracy of estimating foliar biochemical ratios. Hence, the application of integrated multisource data needs further investigation in mapping C:N ratio, especially in rangelands. The successful estimation of C:N ratio depends on the availability of robust algorithms that can improve model accuracy, flexibility, and reduce multi-collinearity problems. This information is important to rangeland managers on reliable, up-to-date data in identifying the limiting nutrients and grazing patterns for effective management of rangelands. This provides a better understanding of population dynamics at various spatial and temporal scales.

Chapter Three: Leveraging Google Earth Engine to estimate foliar C: N ratio in an African savannah rangeland using Sentinel 2 data.

The chapter is based on:

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Leveraging Google Earth Engine to estimate foliar C: N ratio in an African savannah rangeland using Sentinel 2 data

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Abstract

Rangelands are important fodder for livestock and wildlife, and provide a range of ecosystem services to the environment. Foliar nutrients such as nitrogen, carbon, and plant pigments such as chlorophyll can be used as indicators of rangeland stress, and play a vital role in determining their health and productivity. The C:N ratio is a key factor in regulating nutrient utilization efficiency and productivity in plants. Hence, understanding the C:N ratio in rangelands could help herders understand the nutrient limitations, and herbivores distribution to facilitate strategic grazing plans and management. Therefore, there is a need for spatially accurate and up-to-date information on C:N ratio to understand and monitor rangeland health for proactive rangeland management. Remote sensing approaches are spatially explicit, cost-effective, and efficient in monitoring foliar nutrient ratio in rangelands. Whereas, the new generation and advanced Sentinel 2 multispectral sensor has the potential to monitor vegetation health, the strength of its spectral settings in relation to predicting the C:N ratio in rangelands remains largely unexplored. Advanced and freely available Sentinel 2 multispectral sensor (MSI) with specialized red edge bands offer unprecedented opportunities in mapping and monitoring rangeland nutrients. Hence, this study examined the prospect of combined Sentinel-2 (MSI) spectral bands and vegetation indices, and the random forest algorithm to map the C: N ratio within a rangeland. To determine the C:N ratio distribution, the Random Forest and the Boruta variable selection were employed to assess the performance of the combined Sentinel 2 spectral bands and vegetation indices models. Results show an estimated R^2 accuracy of 81 and 74, with RMSE of 2.38 and 2.68 for calibration and validation datasets of the C:N ratio model established by combining the spectral bands and vegetation indices. The random forest variable selection model indicates that the red edge bands, and near-infrared were the most valuable in predicting the C:N ratio. The red edge and near-infrared (Inverted Red-edge Chlorophyll Index) and near-infrared and red band (Enhanced Vegetation Index) vegetation indices were important predictor variables for estimating the C:N ratio. This study demonstrates the prospects and value of mapping the distribution of the C:N ratio in rangelands using high spatial resolution Sentinel 2 MSI. This information not only help determine nutrient deficiencies in rangelands but also provide informed recommendation in mitigating landscape degeneration to allow for rangeland regeneration.

Keywords: rangeland, carbon and nitrogen ratio, Sentinel 2 MSI, spectral bands, vegetation indices.

3.1 Introduction

Forage nutrient concentrations such as carbon and nitrogen play a key role in plant physiological function and health (Munyati et al., 2020, Toor et al., 2021). They affect plants' life cycle, forage nutrition, and palatability to herbivores (Katoch, 2022). In plants, carbon (C) is a major source of energy, which also aids in respiration, photosynthesis, and formation of the structural components of cell walls, such as lignin, cellulose and starch (Cardona et al., 2018, Hu et al., 2022). On the other hand, nitrogen (N) is a major element supporting plant growth, reproduction, and energy storage, important in the photosynthetic process (Mu and Chen, 2021, Dubey et al., 2021). C and N are strongly connected and are important in plant development (Tang et al., 2018b, Martinelli et al., 2021). The carbon and nitrogen ratio (C:N –hereinafter) in plants is a valuable ecological indicator of nutrient absorption, limitation, productivity, and species richness. It influences decomposition and mineralization in the biogeochemical cycle and strongly affects soil organic carbon, and photosynthetic assimilation (Throop et al., 2004, Grechi et al., 2007). Moreover, for sustainable livestock production, the nutrient value of grassland can be classified based on the C:N ratio, which aids in understanding grassland composition and quality. Furthermore, due to a range of factors that include rainfall, grass species types, soil fertility, temperature, and land management, there are differences in the forage nutrients across grass-dominated landscapes, which may in turn affect rangeland quantity and quality, hence carrying capacity (Bondaruk et al., 2022). Therefore, to accurately monitor nutrients in rangelands, a better understanding of the spatial variability of foliar nutrient ratios such as the C: N ratio is necessary. In this regard, understanding the spatial distribution of the C:N ratio can be used to determine a rangeland's nutrient loading and forage health.

Whereas foliar nutrient concentrations such as C and N content can be accurately determined using field sampling and chemical analysis, these approaches are laborious, challenging, and involve destructive sampling, especially at large spatial scales (Ramoelo et al., 2013). Therefore, these approaches are not ideal for the assessment and monitoring of rangeland's health, particularly at large spatial extents. Alternatively, remote sensing techniques offer a non-destructive, fast, and cost-effective approach of acquiring information and estimating rangelands' biophysical and biochemical status, essential for determining rangeland health (Munyati et al., 2022). Specifically, remotely sensed data can be used to detect plant health under different stress conditions as well as determine restoration measures for maximum productivity. Whereas remote sensing has been used to assess nutrients such as C (Pang et al., 2022, Li et al., 2021b) and N (Pullanagari et al., 2021, Pellissier et al., 2015) in grasslands, there are limited studies predicting the C:N ratio in rangelands. For example, Gao et al. (2020a), Beeri et al. (2007), and Phillips et al. (2006) predicted the C:N ratio in rangelands using hyperspectral and multispectral data (Landsat and Aster), while Phillips et al. (2006) predicted the C:N ratio in the Northern Great Plains rangelands using Landsat 5 and ASTER spectral data with RMSE of 3.1 and 1.5, respectively. In another study, Gao et al. (2020a) used hyperspectral data and the random forest algorithm to model the distribution of the C:N ratio in the alpine grassland of China with an accuracy of 85 to 90% at different stages of growth. Beeri et al. (2007) estimated the C:N ratio in a mixed grassland utilizing aerial hyperspectral data with a relative error of 8%. Although, these studies demonstrate the effectiveness of these sensors in monitoring rangeland nutrient status and health, they either used coarse spatial resolution sensors with 16 days' temporal cycle, which are unsuitable for rapid changes in vegetation health (Landsat 5) or costly and spatially restricted (hyperspectral data) sensors, not feasible for rangeland mapping and monitoring, especially in resource-scarce areas like sub-Saharan Africa. Therefore, the most practical sources of spatio-temporal data for modelling the C:N ratio in rangelands are cutting-edge and open-source multispectral sensors.

The advent of advanced multispectral imaging sensors (e.g., Sentinel 2 MSI) provide new opportunities to assess grasslands' health and productivity. The freely available Sentinel 2 MSI is characterized by a 10 m spatial resolution, a 5-days temporal cycle, and a 290 km swath width, which is ideal for regular assessment and monitoring of rangeland health at local and regional scales. Furthermore, it has additional red edge bands within the electromagnetic spectrum that have been demonstrated to enhance vegetation spectral response (Miao et al., 2022, Chabalala et al., 2020a). Although Sentinel 2 data have recently gained prominence in grassland studies, to the best of our knowledge, no study has used it to map the C:N ratio within rangelands. Consequently, it is essential to assess Sentinel 2 MSI's accuracy in predicting the C:N ratio in rangelands. Also, literature indicates that vegetation indices (VI), which are a combination of selected bands, can improve the prediction of foliar nutrients (Koley and Chockalingam, 2022). Vegetation indices, such as the enhanced vegetation index (EVI) for instance, have been used in the estimation of foliar nutrient ratios in rangelands (Ramoelo et al., 2012b, Munyati, 2022). These indices suppress the influence of soil background and atmospheric issues, while improving the signature of vegetation (Mutanga and Skidmore, 2004b, Munyati, 2022). Additionally, there is a dearth in knowledge on novel and distinct indices derived from the red-edge region of the Sentinel-2 MSI in predicting foliar nutrient ratios in grasslands, particularly C:N ratio. Generally, red-edge indices optimize spectral reflectance, which can greatly enhance foliar nutrients prediction accuracy (Gao et al., 2020b, Mngadi et al., 2021a). Ali et al. (2022), Gao et al. (2020b), and Bramich et al. (2021) for instance utilized the red-edge indices (red-edge chlorophyll index and Sentinel-2 red-edge position) in plant nutrients studies. Nevertheless, there is no available literature on the use of Sentinel 2 vegetation indices in predicting C:N ratio, particularly in the savannah rangelands of southern Africa. Hence, it is necessary to test the recently developed red-edge vegetation indices from Sentinel 2 in estimating C:N ratio in a rangeland.

Several studies e.g. Wang et al. (2015a) and Riccardi et al. (2014) have estimated foliar nutrients in grasslands based on different predictors using the linear, multiple, and partial least square regression models. However, these parametric models suffer from overfitting and multi-collinearity in large datasets (Huang et al., 2004, Kokaly, 2001), and importantly, the relationship between spectral data and foliar nutrients are non-linear. Nonetheless, literature shows that non-linear regression models such as the random forest (RF) algorithm developed by Breiman (2001c) have been useful in predicting foliar biochemical properties. This is due to RF's ability to reduce estimation uncertainty and fully integrate spectral information in the model (Han et al., 2022). In addition, the RF can rank the importance of variables contributing to a model. Yang et al. (2021) noted that the RF has an excellent ability to overcome issues of multi-collinearity and to investigate the relationships of specific foliar biochemical and biophysical properties with multiple spectral data.

Recent trends show an increase in the use of cloud computing platforms such as Google Earth Engine (GEE) in the mapping and monitoring of plants' biophysical and biochemical properties (Yang et al., 2021, Mutanga and Kumar, 2019). GEE has the advantage of fast processing and analysis as well as storage of various types of remotely sensed datasets at different spatial resolutions. Hence, it has been widely used in vegetation mapping and monitoring including the determination of grassland biophysical and biochemical properties (Yan et al., 2022). Yan et al. (2022) for instance predicted grassland degradation using random forest and spatial and metrological data in GEE with a mean relative error of 16.9%. Similarly, Xie et al. (2019), Liu et al. (2021a) and Khazieva et al. (2022) mapped and monitored rangeland biochemical and biophysical properties using the GEE platform. The GEE platform is beneficial in understanding the spatial distribution of foliar C:N ratio in rangelands due to its powerful data processing, efficient computing analysis and storage in the cloud, necessary for accurate and timely vegetation monitoring. Despite, the accuracy of these studies, there are limited studies on the use of the GEE platform in predicting foliar nutrients. In this study, we leverage the use GEE big data processing platform to detect the C:N ratio using Sentinel 2 datasets and random forest algorithm. Hence, this study sought to investigate the value of Sentinel 2 data and the RF algorithm, combined with field data in estimating the C: N ratio in a rangeland. Our objectives were, firstly, to explore the strength of Sentinel 2 spectral bands and vegetation indices in retrieving the C: N ratio, and secondly, to determine the spatial distribution of the C: N ratio within a rangeland.

3.2 Materials and methods

3.2.1 Field survey and data collection

Field data were collected in summer (i.e. 28th of March to the 1st of April) at peak biomass, with maximum productivity to decouple the effect of biomass on C:N ratio (Mutanga and Skidmore, 2004b). A total of 120 pre-determined random sampling locations inserted in a handheld Global Positioning System (GPS) with sub-meter precision was used to locate the sampling sites. Using the random point as a centroid, a plot size window of 10 x 10 m was constructed and two subplots of 1 x 1m were randomly selected within the constructed plots to obtain variability. In each subplot, grass samples were clipped and the wet biomass measured using a calibrated digital scale, placed in brown envelopes, and labelled for laboratory analysis. Furthermore, in each sub-plot, conventional grassland observations such as geographic location, vegetation coverage, and percentage of photosynthetically active vegetation were recorded.

The grass samples in each envelope were then oven dried at 65 °C for 48 hours, weighed to obtain biomass, then milled, and sieved. The C and N contents (g 100 g1) on 2 mg of the dry powder of each sample were measured using an elemental analyser with a combustion temperature of 950 °C and a reduction temperature of 640 °C. The analyser can simultaneously determine the levels of C and N in samples. Forage C:N ratios are estimated as the proportion of C to N contained in forage on a weight basis (Xu et al., 2018, Gao et al., 2020a).

3.2.2 Image acquisition and pre-processing

Google Earth Engine (GEE) is a cloud computing platform that provides an easily accessible and user-friendly interface for developing interactive data and algorithms. Within the GEE platform, Sentinel 2 data are accessible in two different levels depending on the atmospheric correction status: Level 1C for top-of-atmosphere (TOA) images, and Level 2A for bottom-of-atmosphere (BOA) reflectance. Level 1C for top-of-atmosphere (TOA) images requires third party application to obtain the reflectance values for vegetation analysis (Schmitt et al., 2019). A single Level 2A image with radiometric, atmospheric, and spatial registration on the global referencing system was imported using the GEE data pool (https://code.earthengine.google.com) (Gorelick et al., 2017). Using the filter function within the code editor, the image was filtered to the boundary of the study area, from the 28th of March to the 1st of April, with a cloud cover specification of less than 5%. Sentinel-2 bands used for vegetation analysis, include; blue-b2 (490), green-b3 (560), red-b4 (665), red-edge-b5 (705), red-edge-b6 (740), red-edge-b7 (783), near-infrared-b8 (842), near-infrared-b8A (865), shortwave infrared-b11 (1614) and shortwave infrared-b12 (2190). Furthermore, the processed image was used to calculate vegetation indices (Table3.1) ideal for vegetation analysis (Sharifi, 2020, Mngadi et al., 2021a, Gao et al., 2020b).

Table 3.1 Sentinel 2MSI spectral vegetation indices adopted for the study.

Spectral indices	Formula	References
Normalized difference vegetation index (NDVI)	$\frac{NIR - Red}{NIR + Red}$	(Ghosh et al., 2018)
Normalized difference infrared index (NDII)	$\frac{NIR - SWIR}{NIR + SWIR}$	(Klemas and Smart, 1983)
Green normalized difference vegetation index (GNDVI)	$\frac{NIR - Green}{NIR + Green}$	(Ghosh et al., 2018)
Enhanced vegetation index (EVI)	$2.5*[\frac{NIR - Red}{(NIR+6*Red-7.5Blue+1)}]$	(Cavalaris et al., 2021)
Wide Dynamic Range Vegetation Index (WDRVI)	$\frac{0.3 * NIR - Red}{0.3 * NIR - Red}$	(Sun et al., 2019c)
Sentinel-2 Red-Edge Position (S2REP)	$\frac{705 + 35 * (Red - RedEdge3)}{(2 - Red)/(RedEdge2 - (RedEdge)}$	(Ali et al., 2022)
Normalized difference red-edge 1 (NDRE1)	$\frac{RedEdge2 - Red}{RedEdge2 + Red}$	(Gao et al., 2020b)
Chlorophyll-red edge based index (CI red-edge)	$\frac{RedEdge3}{RedEdge} - 1$	(Gitelson et al., 2005)
Inverted red-edge chlorophyll index (IRECI)	$\frac{RedEdge3 - Red}{RedEdge3 + Red}$	(Majasalmi and Rautiainen, 2016)
Normalized difference red-edge 2 (NDRE2)	$\frac{RedEdge2 - Red}{RedEdge2 + Red}$	(Gao et al., 2020b)
Chlorophyll green (Cl green)	$\frac{RedEdge}{Green} - 1$	(Madonsela et al., 2022)
Red edge chlorophyll index 1(RECI1)	$\frac{NIR}{RedEdge} - 1$	(Gitelson et al., 2005)

3.2.3 Statistical analysis

3.2.3.1 The random forest algorithm

The regression analysis was conducted using the Random Forest (RF) algorithm to predict the correlation between the C:N ratio and Sentinel 2 spectral bands and derived VI. RF is an ensemble machine learning algorithm that builds many decision trees (*ntree*) and chooses the best trees through majority vote for model predictions (Breiman, 2001c). RF reduces model variance without increasing bias, enhances accuracy, and reduces overfitting by employing a bootstrapping technique (Cai et al., 2020). To determine the split at each tree node, an ensemble model uses a modified feature bagging technique to select a random subset of features (*mtry*). Model nodes represent predictor variables, while response variables are selected subsets of data. An evaluation of all predictors at each node is first performed then a random selection of the best split is made (Breiman, 2001a). Additionally, random forest enables model optimization to enhance results by combining two parameters, namely *ntree*, which makes use of several decision trees and bootstrap training samples, and *mtry*, which takes into account the predictor variables within each tree node (Sibanda et al., 2021). According to Fernández-Habas et al. (2022), the smallest out-of-bag error (OOB) determines the optimal *ntree* and *mtry* values for the best prediction model. The total dataset (n = 120) was randomly split into 70% (n = 84) as training data and 30% (n = 36) as testing datasets. In this study, 70% of the sample (in-bag samples) was used as training data, while 30% of the samples (OOB) were used to validate the model. Within the GEE, the RF model is commonly referred to as a classifier. However, the "setOutputMode" property which decides the type (i.e., classification or regression) of modelling when training, must be set to "REGRESSION" when performing a regression analysis. The general regression documentation within the GEE for RF is given below: *ee. Classifier.smileRandomForest* (*numberOfTrees, variablesPerSplit, miniLeafPopulation, bagFraction, maxNodes, seed*).

where: *ee. Classifier.smileRandomForest* = the RF model, *numberOfTrees (Integer)* = the total decision trees to produce; here 400 was selected for optimal output after testing a range between 100 to 1000 with an interval of 100, *variablesPerSplit (Integer, default: null)* = total variables per split; if unspecified uses the square root of the numbers of variable, *miniLeafPopulation (Integer, default: 1)* = creates nodes only if their training set consists of these many points.

3.2.3.2 Optimal Predictor Variable Selection

Multicollinearity due to the high interrelationships between predictors is a common problem with regression models (Odebiri et al., 2020). Consequently, a variable selection is ideal to remove redundant variables and produce the best possible outputs. In this study, the Boruta variable selection strategy was adopted to select the best optimal variables for the C:N ratio simulation. The Boruta algorithm is a wrapper approach developed around the RF algorithm (Breiman, 2001a, Poona and Ismail, 2014).

In Boruta, each input predictor is given a Z-score with respect to the shadow attribute. Variable importance is decided by shadow bands, which act as reference points (Kursa et al., 2010). A RF regression is then performed, with each band's importance evaluated. The number of times a band has higher importance than the maximum Z-score among shadow bands is recorded. When a band's frequency is much higher than the expected value, it is judged "important," whereas if it is significantly lower, it is deemed "unimportant" and deleted. In this study, the Boruta variable selection was conducted in the R, version 4.2.1 environment (Kursa and Rudnicki, 2010).

3.2.3.3 Accuracy assessment

RF model performance was assessed utilizing the coefficient of determination (R^2), and root mean square error (RMSE). RMSE is the difference between the field measurements and the predicted C:N ratio values, while R^2 represents the percentage of the response variable variation (Jaber et al., 2011).

3.3 Results

3.3.1 Descriptive statistics

Based on the descriptive statistics, the minimum and maximum values of the measured C:N ratio within the rangeland are 14.21 and 40 with a standard deviation of 5.21 and a mean of 22.7.

3.3.2 Variable Importance Selection

Figure 3.1 shows that the NIR band (8a), red edge bands (6 and 7), IRIEC and EVI were influential to the model. Figure 3.2 shows the Boruta variable selection graph. The blue boxplot represents the Z- score of the shadow variable. Red boxplots indicate variables that were rejected, whereas green boxplots show Z-scores for confirmed variables. The graph demonstrates that green variables are more significant than shadow variables, which are represented by blue lines, and have higher values. Figure 3.3 shows the optimal variables in modelling the C:N ratio using Boruta algorithm, and their ranking in terms of importance. The most influential variables using the Boruta were red edge bands (6 and 7), NIR (8a), and the IRIEC vegetation index.

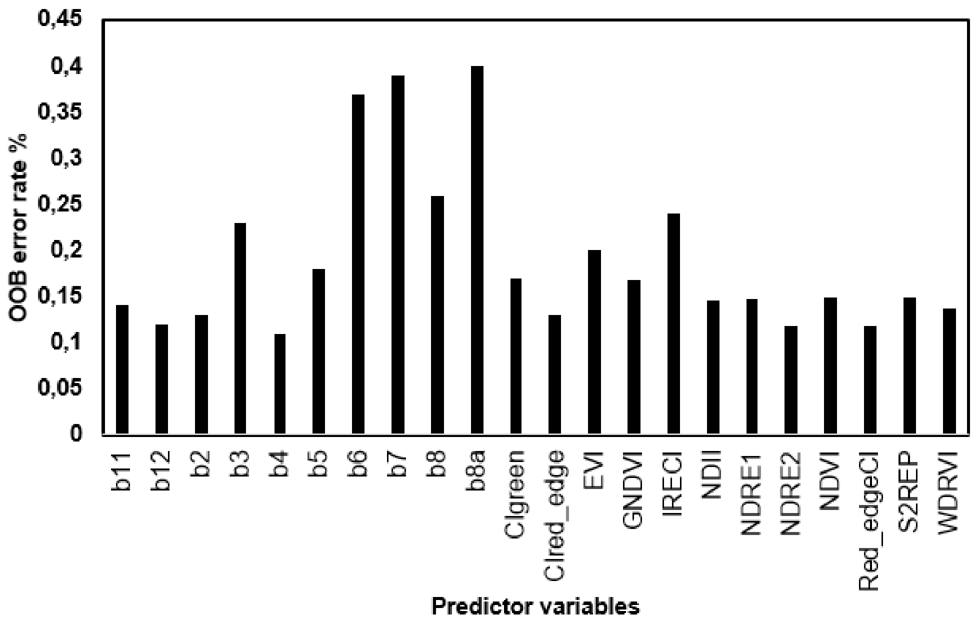


Figure 3.1: Variable importance in predicting the C:N ratio using the OOB in random forest

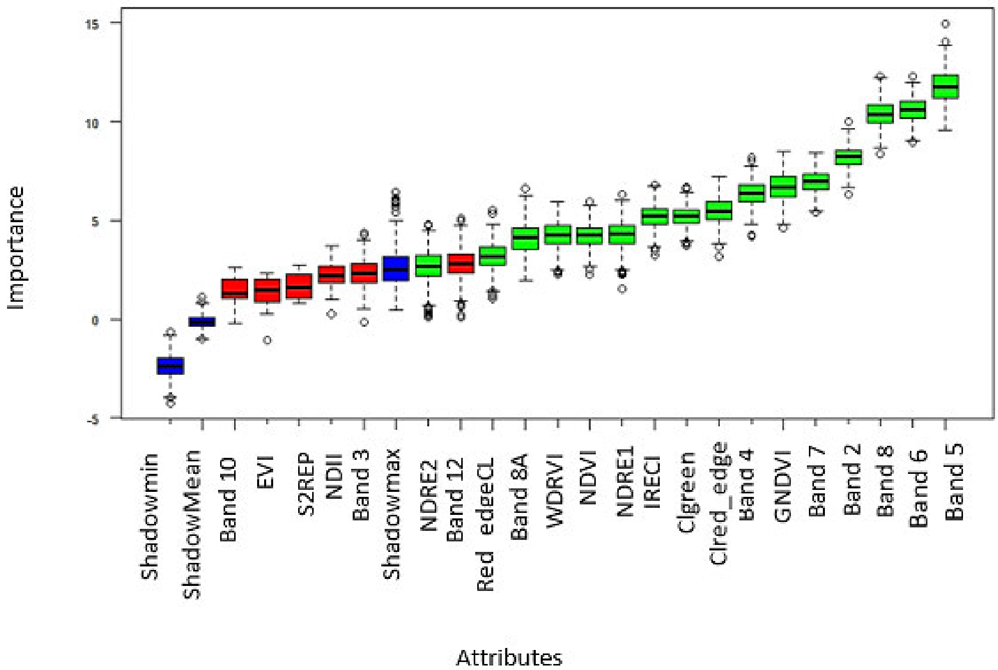
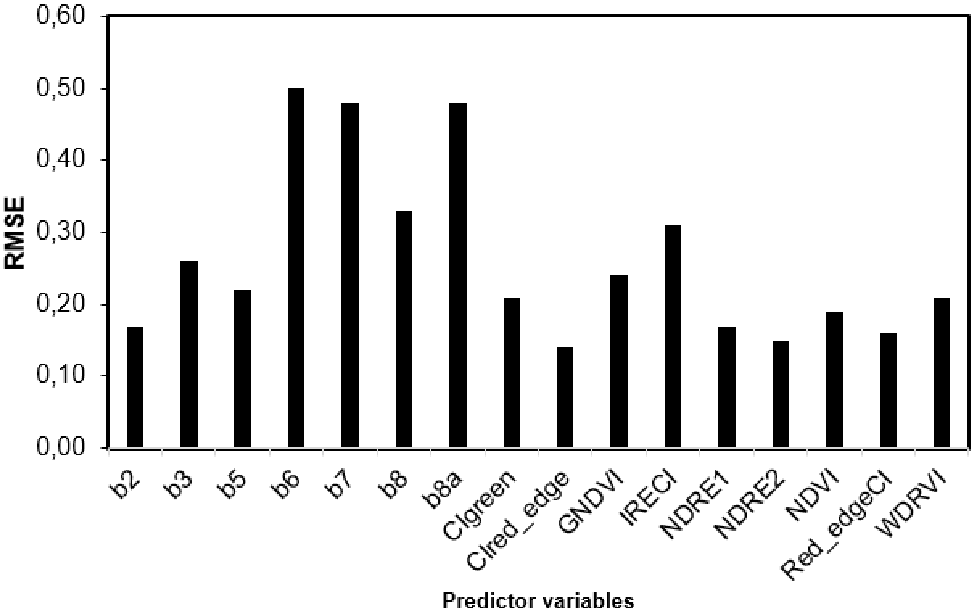


Figure 3.2: Variable selection by Boruta algorithm, green bars indicate the selected variables, and the red bars indicate rejected variables.



3.3.3 Evaluation and performance of models

Figure 3.4 shows the relationship between predicted and measured C: N ratio using random forest. The calibration dataset (A) generated an RMSE of 2.38, R^2 of 0.81 and MAE of 1.19, whereas the validation dataset(B) produced RMSE of 2.68, R^2 of 0.74 and MAE of 1.34. Figure 3.5 shows the relationship between predicted and measured C: N ratio for calibration (A) and validation (B) datasets using Boruta variable selection. The calibration datasets produced an RMSE of 2.38, R^2 of 0.80, and MAE of 1.19. Meanwhile, the validation datasets revealed an RMSE of 2.87, R^2 of 0.69, and MAE of 1.43. However, the Boruta variable selection did not improve our model accuracy, hence the model using the OOB in RF was adopted in the final model prediction.

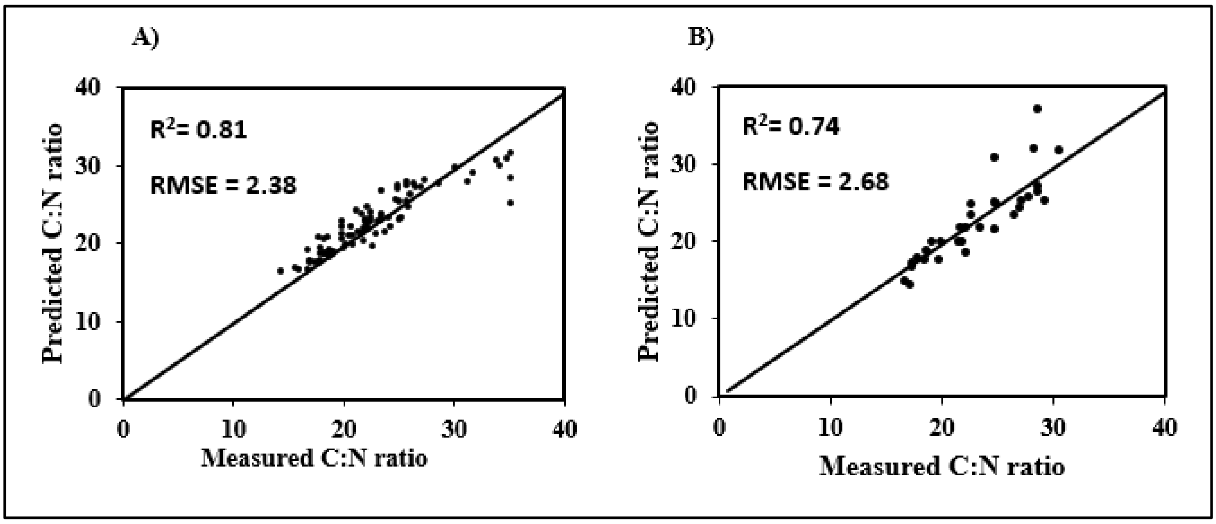


Figure 3.4: Relationship between the predicted and observed C:N ratio in the study area for calibration (A) and validation (B) data using random forest.

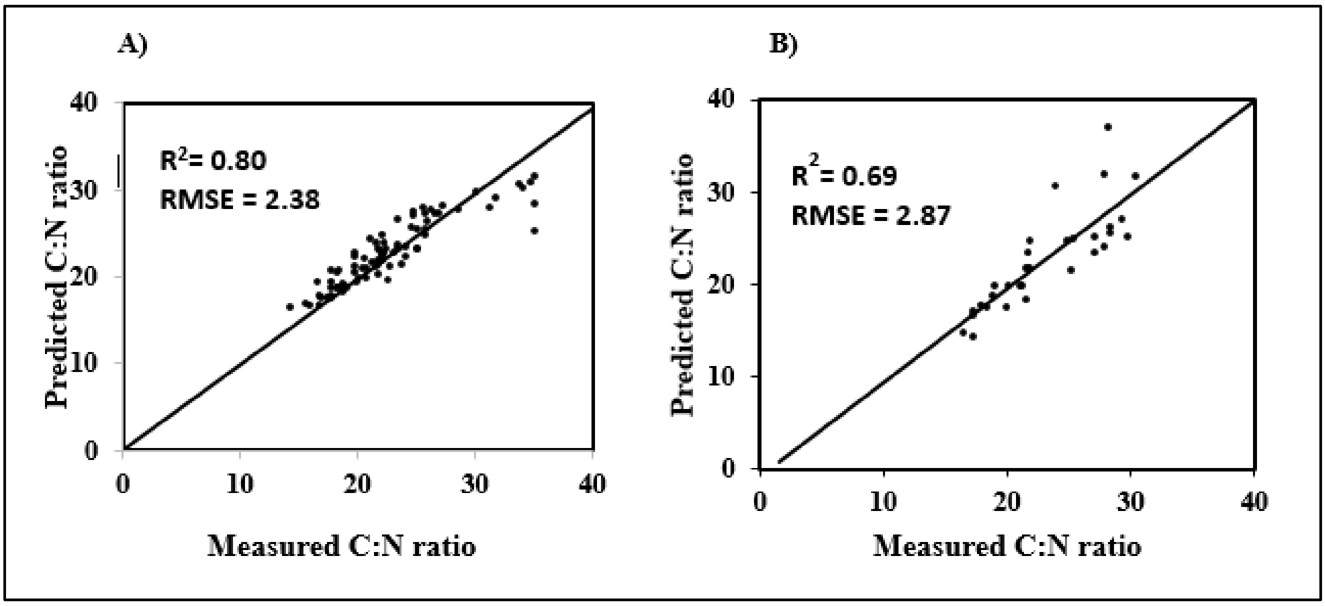


Figure 3.5: Shows the relationship between predicted and measured C:N ratio for calibration (A) and validation (B) data using Boruta variable selection.

3.3.4 Mapping the C:N ratio

Rangeland managers and policymakers can use the spatial distribution map of the C:N ratio to identify grasslands with nutrient deficits, which is crucial for setting appropriate restoration goals, and mitigating landscape degradation to allow for rangeland regeneration. The results indicate that the predicted C:N ratio of the rangelands ranges from 16.39 (low) to 32.12 (high) in Vulindlela. Overall, the C: N ratio distribution in the study area is high in the western part of the rangeland, and low in the north-eastern and south-eastern parts of the rangeland.

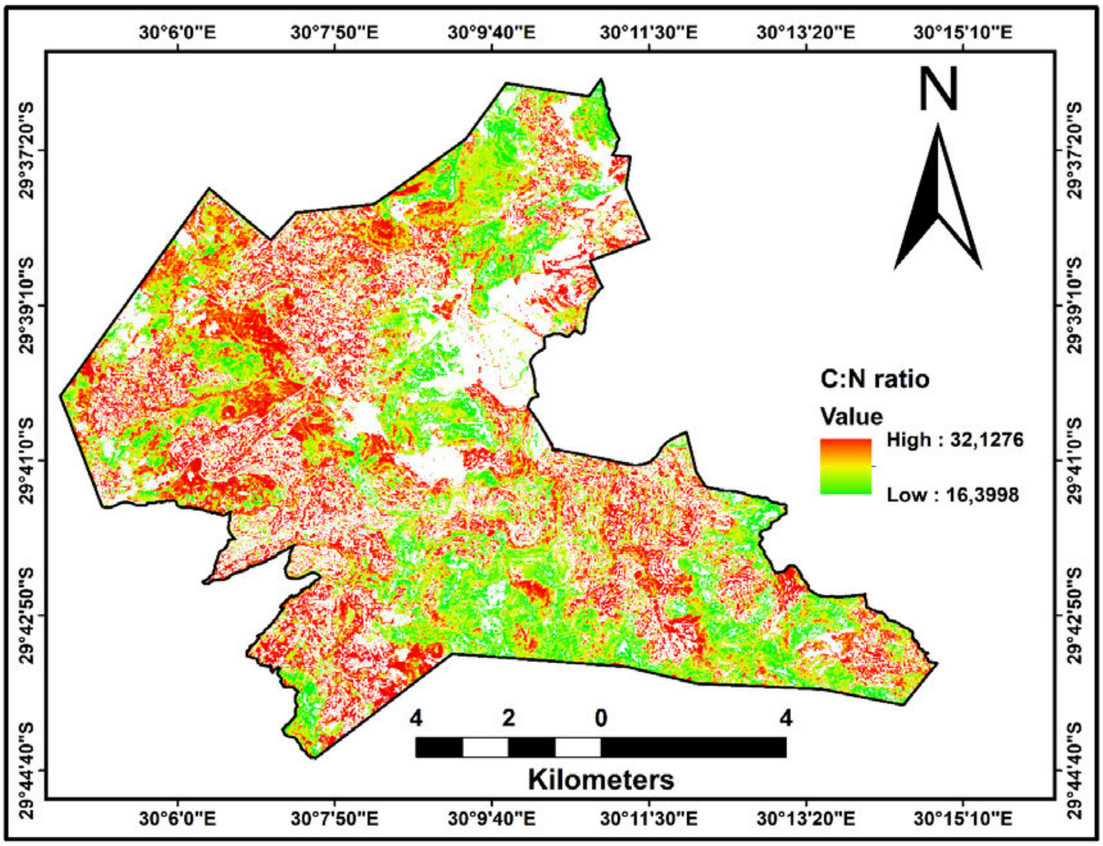


Figure 3.6: Spatial distribution of the C:N ratio in Vulindlela communal rangeland using Sentinel 2 and random forest algorithm.

3.4 Discussion

Accurate and continuous monitoring of C:N ratio is important in understanding rangeland health and productivity. As a result, detailed modelling techniques capable of estimating and monitoring nutrients in rangelands have become important. Therefore, our study investigated the use of Sentinel 2 MSI bands and VI in predicting the C: N ratio in rangeland.

The results showed that Sentinel 2 spectral data could be used to retrieve the C:N ratio in the rangeland with a mean of 22.7 and 23.18, an R^2 of 81 and 74, RMSE of 2.38 and 2.68 using the training and validation datasets, respectively. In the feature selection method using the Boruta algorithm, the model accuracy did not improve. According to Kaneko (2021) the Boruta prediction accuracy in the regression model can be attributed to the limited number of data in the feature selection, and choice of data in the model. The reasonable predictive performance of the RF model can be attributed to the Sentinel 2 strategically positioned bands, especially the red-edge bands. Its inclusion as a predictor variable improved the C:N ratio modelling accuracy, due to its ability to detect various leaf properties such chlorophyll, and carbon constituents which are important for foliar nutrient estimation (Ali et al., 2022, Clevers and Gitelson, 2012, Gao et al., 2020b). The resultant model shows that C:N ratio ranges from 16 to 32. The C:N ratio in this study were relatively similar to the C:N ratio found in literature for rangelands (Phillips et al., 2006, Beeri et al., 2007). For instance, Phillips et al. (2006) discovered that fertilized/lightly grazed *A. desertorum* had a lower C:N ratio 23 ± 4.4 in comparison to heavily and moderately grazed rangelands with a C:N ratio of 31.3 ± 4.4 and 31.3 ± 5.5, respectively.

The results from this study suggest that there is a strong correlation between the spectral reflectance of the near-infrared and red edge bands in predicting the C:N ratio in plants. Absorption features sensitive to C compounds (i.e. sugar, lignin, cellulose, and starch) in vegetation are located in the NIR and SWIR spectrum (Curran, 1989, Kokaly and Clark, 1999). Based on the studies by Sibanda et al. (2015) and Curran et al. (2001), the influence of the NIR region can also be attributed to the high levels of nitrogen, resulting in increased biomass density, and leaf area index. Also, the NIR region is sensitive to the leaf surface and internal structure, critical for detecting plants' health and productivity (Mutanga and Skidmore, 2004a, Zahir et al., 2022). Furthermore, Schlemmer et al. (2013) reported that retrieval of N in forage is related to the absorption of chlorophyll, and includes the red edge and NIR regions, which are related to chlorophyll detection. Specifically, the strategically located red edge bands (740,780nm) in Sentinel 2 contributed significantly to the model. The red edge region is particularly sensitive to foliar properties including chlorophyll, protein, cellulose, sugar, lignin, leaf area index and biomass (Ramoelo et al., 2015b, Liu et al., 2022a), necessary in determining rangeland C:N ratio. Previous studies show that bands in the NIR and red-edge region can predict the C:N ratio, since the ratio is correlated with N, chlorophyll, cellulose, and lignin contents of plants (He et al., 2006a, Xu et al., 2018). As a result, it is possible to accurately detect the C:N ratio in grasslands using spectral variables sensitive to the retrieval of C and N in plants. The results of this study are comparable to those of Durante et al. (2014), Xu et al.

(2018), and Gao et al. (2020a) who reported that the NIR bands and red edge bands were highly influential in predicting the C:N ratio in plants. For instance, Xu et al. (2018) reported that the spectral slope features from the red edge and NIR region could detect the C:N ratio in wheat and barley leaves using the Branch and bound algorithm. Gao et al. (2020a) also demonstrated that the red, red edge and SWIR regions performed well in predicting foliar C:N ratios, with coefficients of determination of validation (V-R^2) ranging from 0.70 to 0.80 using hyperspectral data with random forest and support vector machine. Similarly, Durante et al. (2014) identified absorption bands in the red, red-edge, and SWIR regions that could predict the C:N ratio in grass using leaf spectral reflectance.

IREC vegetation indices (a combination of the red edge and NIR bands) were valuable in detecting the C:N ratio in the rangeland. As opposed to standard NDVI, red-edge derived indices are less prone to saturation, thus can be used on dense vegetation. Also, red edge indices are less sensitive to soil background, and atmospheric effects (Clevers and Gitelson, 2013), and red edge bands are closely related to chlorophyll (Chemura et al., 2018). Therefore, we conclude that the biological connections between N, chlorophyll, and canopy structure can account for IREC's outstanding performance. The findings in this study are consistent with Munyati et al. (2020), who found that VI derived from the red edge bands in Sentinel 2 could be used to monitor N and other macronutrients in the savannah grassland. Westergaard-Nielsen et al. (2021) quantified the spatiotemporal variations in Arctic tundra leaf C:N ratio based on the new Sentinel 2 derived index. The results showed that the red-edge index (NRI_{1610}) estimated the C:N ratio with an $R^2 = 0.81$ accuracy. In these studies, red-edge indices were effective at measuring vegetation productivity and health. This is further supported by the fact that the strength of the IREIC is derived from a relationship of bands (i.e., red edge and NIR) to boost the spectral influence from vegetation, while concurrently suppressing the soil background, sensor viewing angle, and atmosphere. The EVI constructed from the NIR, red and blue bands were important in our model. Compared to the NDVI, the EVI developed by Huete et al. (1994) is more sensitive in densely vegetated areas, by decoupling background signal, atmospheric and soil effects. EVI is an important indicator of greenness (vigour) in plants and can provide valuable information on forage quality. Spectral information in the visible (blue and red region) possesses high predictive power capable of estimating biochemical concentration in forage (Rowhani et al., 2011). The EVI is popular in detecting spatiotemporal vegetation patterns such as degradation and productivity in vegetation (Kibret et al., 2021).

The spatial variability of the C:N ratios across the study area were observed to be highest in the north-eastern and south-eastern grasslands. The C:N ratio spatial variability in the study area can be attributed to various factors that include topography, rainfall, temperature, and soil nutrients (Fu et al., 2022b, Barbehenn et al., 2004), which regulate vegetation productivity and health. For instance, topographic variables (i.e., slope, elevation, aspect) have been reported to affect the distribution of foliar nutrients within grasslands (Hoover et al., 2021, Lieffering et al., 2019). Also, variations in the C:N ratio can be caused by differences in aspect, species type, canopy structure, and leaf area index (Mogashoa et al., 2021, Xu et al., 2019). For example, C3 and C4 grasses have different forage nutrient statuses, and their response to climate changes differs (Adjorlolo et al., 2015, Barbehenn et al., 2004). Additionally, the choice of grassland management practices such as grazing intensity, mowing, burning and fertilization affect the grasslands' biophysical and biochemical properties (Mayel et al., 2021). In different studies, Phillips et al. (2006) and Gao et al. (2020a) found that grazing, fertilizer application, and seasons affected the models' predictive accuracy of the C:N ratio on pastures at the landscape scale.

In summary, this study indicates that freely available advanced multispectral sensors such as Sentinel 2 with the RF algorithm can effectively predict foliar nutrient ratios in large and heterogeneous landscapes. The strength of RF lies in its ability to handle different predictor variables and choose the important variables needed for the best regression model (Li et al., 2022a). This study demonstrated that the C:N ratio, as an indicator of nutrient limitation, can provide valuable information to rangeland managers and ecologists on how nutrient limitations influence the feeding patterns and population dynamics of grazing animals at both local and regional scales, information that is important for proactive planning and management of rangelands. Furthermore, we propose the inclusion of physical and environmental variables in future research to test their influence on the spatial variation of foliar nutrients ratios. In addition, future investigations on the spatial distribution of the C:N ratio across different seasons is required. Finally, future research should test the strength of new generation sensors with high spatial resolution sensors such as Planetscope Dove, as well as the fusion of different sensors in estimating the C:N ratio. However, the study was limited by the few sampling points that were used in the analysis, due to the area's topography. Increasing the sampling points might increase the model accuracy.

3.5 Conclusion

This study evaluated the prospects of Sentinel 2MSI spectral data and RF to estimate the forage C:N ratio of rangeland. Based on the results, we conclude that the spectral signature from Sentinel 2 MSI can be reliably used to determine the C:N ratio in a savannah rangeland. Furthermore, Sentinel 2 bands in the red edge regions and NIR have valuable contributions towards predicting the forage C:N ratio. The findings indicate that Sentinel 2 bands and vegetation indices can be used to directly retrieve C:N ratio in grassland at both local and regional scales, hence providing an effective framework for the continuous monitoring and mapping of C: N ratio within South African grasslands using a relatively high-resolution data (Sentinel 2). This information is important to rangeland managers for effective and timely monitoring of rangelands.

Chapter Four: Fusion of Planetscope and Sentinel 2 in assessing foliar C:N ratio in a rangeland

This chapter is based on;

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Fusion of PlanetScope and Sentinel 2 in assessing foliar C:N ratio in a rangeland

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Abstract

Efficient monitoring of foliar nutrient such as the C:N ratio is important for sustainable rangeland productivity. Recent advancement in earth observation technology provides multispectral sensors with high spatial, spectral and temporal resolution suitable for modelling foliar nutrients. However, the estimation of foliar nutrients such as C:N ratio using optical sensors are often limited due their spatial, spectral, radiometric, and temporal resolutions. Whereas the fusion of optical spectral data has the potential to reduce these challenges, no studies have utilized fused datasets in mapping forage C:N ratio in heterogeneous landscape at a fine scale. Hence, this study examined the strength of fusing Sentinel 2 and Planetscope datasets in enhancing the estimation of foliar C:N ratio in a heterogeneous landscape at a fine scale. To achieve this, Planetscope and Sentinel 2 datasets were fused using the pixel fusion technique and the random forest algorithm to map the foliar C:N ratio. The results show that the C:N ratio estimates of Planetscope was R^2 of 0.60, and RMSE of 3.40. Sentinel 2 dataset provided a better model accuracy with R^2 of 0.70, and RMSE of 2.82. The best C:N ratio model accuracy (R^2 of 0.79 and RMSE of 2.36) was generated from the fused dataset. This finding is vital for understanding the value of image fusion in enhancing rangeland nutrients estimation for optimal productivity. The study concludes that the fusion of optical sensors in rangeland management requires further investigation.

Key words: C:N ratio, rangeland, Sentinel 2, Planetscope, image fusion, random forest regression.

4.1. Introduction

Rangelands contribute significantly to food security and economic well-being, as they provide fodder for animals and support rural communities (Timpong-Jones et al., 2023b, Naghizadeh et al., 2022). They also provide an array of ecosystem services to the environment such as climate change mitigation, carbon sequestration, water regulation and plant pollination (Masenyama et al., 2023). However, despite their value, rangelands suffer from degradation due to a variety of factors including climate change, population growth, invasive species, and poor land management (Sainnemekh et al., 2022). In rangelands, pasture degradation affects livestock production and food security, especially forage quality and quantity (Bolo et al., 2019). Rangeland productivity and nutrient cycling in ecosystems can be inferred from biochemical concentrations in leaves (Kumar et al., 2021). Grass nutrient levels such as, carbon (C) and (N) are important nutrients for plant development and metabolism, which influence grazing pattern and wildlife distribution (Toor et al., 2021, Wang et al., 2021c). Nitrogen is a major constituent of chlorophyll and plant cellular constituents and plays an important role in plant development and net primary productivity (Leghari et al., 2016). On the other hand, C is a major source of energy and the building block for plants, and essential in plant productivity (Smith and Stitt, 2007). The amount and level of nitrogen in plants affects the photosynthetic pathways, respiration and ultimately biomass production (Tang et al., 2018a). Over time there are changes in the C and N levels due to factors such as topography, grazing, climate, and land use (Fu et al., 2022a, Mokgakane, 2021). The changes in C and N lead to variation in nutrient ratio (C:N ratio), which affects the nutrient cycling and rangeland productivity.

In rangelands, foliar nutrient ratios have been used as an index to identify the availability and limitations of nutrients (Ramoelo et al., 2011, Gao et al., 2020a). This method is well established in the field of ecological stoichiometry, which investigates the balance and relationship of elements in ecological processes. In rangelands, the C:N ratio affects photosynthesis, ecosystem balance, and aids in the regulation of litter decomposition (Durante et al., 2014, Gao et al., 2020a). Additionally, the C:N ratio is a measurable indicator in classifying forage nutrients at a landscape scale, that can be used at regional scale to determine rangeland quality during the growing season, litter quality at senescence, carbon assimilation, wildlife grazing and distribution, climate change and soil organic matter; which is crucial in understanding precision animal husbandry (Li, 2004). According to Beeri et al. (2007), grazing animals in rangelands require plants with a high protein content and a low C:N ratio (<36g of carbon for every 1g of nitrogen). To optimize rangeland resource utilization and diagnose forage growth status, it is useful to investigate the spatial distribution of the C:N ratio.

At a landscape scale, foliar nutrients in grassland vary in response to different factors that include, climate, grazing pattern, soil properties and site-specific edaphic conditions (Catorci et al., 2021, Liu et al., 2022c). The interrelation of these factors, create a patchy distribution of pasture nutrients made up of different grass species on the landscape (Jing et al., 2022). Due to the fine-scale nature of the variation, there is a need for high spatial and temporal coverage in mapping grasslands, while detecting their minute variations. Therefore, techniques that offer continuous, and accurate data sources at a fine scale, at different spatial scales are important to provide rangeland managers with objective information on grassland quality and productivity over space and time. The traditional approach of monitoring the foliar N and C in plants are based on field measurements, and laboratory analysis (Motsara, 2015). Though these traditional approaches have high precision, they are time consuming, costly, and susceptible to errors due to bias in data collection (Bolster et al., 1996). Hence, sensors with high spectral and spatial resolutions can minimize these errors and identify features with similar properties in plants (Minaei et al., 2022, Zhang et al., 2023).

Remotely sensed data (RS) have proved to be an invaluable source of proximal data for estimating different biochemical properties, such as C:N ratio of rangelands under different spatial scales (Badreldin et al., 2021, Wang et al., 2022). RS can detect various biochemical attributes in plants such as chlorophyll, nitrogen, cellulose, starch and lignin (Ramoelo et al., 2015c). The majority of previous research, however, has focused on quantifying chlorophyll, carbon (C), and nitrogen (N) in grasslands (Pang et al., 2022, Adjorlolo et al., 2014). Few studies have investigated the use of remotely sensed data to estimate the foliar C: N ratio, which is important in rangeland management (Phillips et al., 2006, Gao et al., 2020a, Berri, 2007). For instance, Phillips et al. (2006) estimated the C:N ratio in the Northern Great Plain rangelands under variable canopy moisture conditions using Aster and Landsat 5 spectral data with an RMSE of 1.5 and 3.1, respectively. In another study, Rahman et al. (2020) utilized Landsat 8 and Landsat 5 TM to map the spatiotemporal variability of the C:N ratio of senescent leaves in a forest in Bangladesh using different machine learning algorithms (random forest, stochastic gradient boosting, support vector machine) with reasonable accuracies. Despite the results, the spatial, spectral and temporal resolutions might not be ideal in detecting rapid changes in heterogeneous landscape, especially at a fine scale. For example, Landsat 5 has a

16-day temporal resolution and 30m spatial resolution which might be ideal in detecting rapid changes in grassland at a landscape scale.

Recent advancements in remote sensing technology have seen the introduction of multispectral sensors with high spatial and spectral resolution with specialized red edge bands that are more sensitive in detecting biochemical properties in plants. In particular, open-source Sentinel 2 MSI has a spatial resolution of 10m to 60m, with thirteen spectral bands inclusive of three edge bands that are suitable for nutrient monitoring in vegetation (Abdullah et al., 2019, Ali et al., 2022, Gao et al., 2020b). Despite Sentinel 2's popularity, few studies have used it to map foliar nutrient ratios in grasslands (Arogoundade et al., 2023d, Gao et al., 2020b). For instance, Arogoundade et al. (2023d) utilized Sentinel 2 bands and vegetation indices with the random forest algorithm to predict the C:N ratio in South Africa. The results yielded an R^2 of 74% with the red edge and near infrared indicated as optimal variables in C:N ratio prediction. Similarly, in Gansu Province, China, Gao et al. (2020b) estimated forage N:P ratio integrating Sentinel 2 bands and VI with R of 0.49 and 0.59 at the peak of biomass and senescing period respectively, using the random forest algorithm. The aforementioned studies noted that spectral bands contributed to the model accuracy in estimating the grassland nutrients. Nevertheless, Misra et al. (2020) reported that the utility of multispectral sensors such as Sentinel 2 is frequently limited by clouding, shadow effects, and poor atmospheric conditions. As a result, the available S2 images may exceed the 5-day temporal cycle for a specific region. Kluczek et al. (2023), Hardy et al. (2021) and Li and Roy (2017) in different studies noted that spectral signatures of the same species can differ depending on topographic locations and varying climatic factors, thereby affecting the spectral responses from the sensors. Due to the heterogeneous nature of rangelands, high spatial resolution multispectral sensors are an advantage in detecting the minute differences in the spatial distribution of the C:N ratio at a landscape scale.

High spatial resolutions nanosatellites such as Planet scope (PS) offer the opportunity to partially overcome the spatial resolution limitations associated with medium-resolution sensors, especially in heterogeneous landscapes (Andreatta et al., 2022, Zhao et al., 2022, Purnamasari et al., 2021, Kluczek et al., 2023). PS has a fine spatial resolution of 3.7m and 1-day temporal cycle, which is capable of capturing and discriminating the biophysical and biochemical attributes of grasslands at finer scales (Pereira et al., 2022, Andreatta et al., 2022). Similar, to its predecessor, Dove classic (Huang and Roy, 2021), the newly launched Super Dove Planet scope has 4 spectral bands (red, green, blue and near infra-red), as well as 4 additional bands (coastal blue, green 1, yellow, and red edge) (Frazier and Hemingway, 2021) capable of improving foliar nutrient ratio prediction at fine scale. For instance, Vasudeva et al. (2021) and Ramoelo et al. (2015c) demonstrated the sensitivity of the red edge bands to foliar nutrients such as nitrogen, chlorophyll, and carbon-based constituents using Sentinel 2 and Worldview 2 datasets, respectively. However, the new Super Dove Planet scope has not been extensively applied in foliar nutrient studies, especially to estimate the C:N ratio in rangelands.

Despite PS's superior spatiotemporal resolution, it suffers from radiometric inconsistencies in comparison to the larger conventional satellites such as Landsat series or Sentinel 2 (Sadeh et al., 2021). This is attributed to its low signal-to-noise ratio, and difficulties with inter-calibration (Houborg and McCabe, 2018). As a result, the fusion of the spatial and spectral properties of these sensors may overcome the constraints outlined previously and has attracted significant interest as a new way of estimating forage yield and quality. This is because different spectral measures for the same target of interest may be produced by different remote sensing platforms due to differences in the spectral, spatial, and radiometric resolution specifications they offer (Jensen, 2009). For instance, in Brazil, Pereira et al. (2022) established that the spatial resolution of Planetscope (3m) was more beneficial than Sentinel 2's spectral bands (13) in predicting the spatial distribution of nitrogen in a grazing area. However, Sadeh et al. (2021) in Australia reported that the fusion of Sentinel 2 and PS into a high spatiotemporal image with the spectral quality of Sentinel 2 improved the prediction accuracy of wheat health and growth with an RMSE of 1.37. Previous studies have focused on using multi sensor fusion in predicting C, or N in grasslands, crops or forest (Grüner et al., 2021, Lapaz Olveira et al., 2023, Myrgiotis et al., 2020). However, there remains a dearth in research on the value of fusing multispectral sensors such as Sentinel 2 and Planetscope for C:N prediction, especially in heterogeneous landscapes at a fine scale.

In addition, studies such as Teltscher and Fassnacht (2018), Hu et al. (2023) and Kearney et al. (2022) have highlighted the importance of spectral derivatives from multispectral data such as vegetation indices in modelling foliar biochemical. In unrelated studies Ghimire et al. (2020) and Xu et al. (2023) demonstrated that vegetation indices derived from fused images improved the quality of vegetation mapping. However, to the best of our knowledge, no study has investigated the accuracy and information contained within fused vegetation indices in modelling the C:N ratio within a rangeland. Due to the complexity and heterogeneous nature of rangelands, it is paramount to test whether spectral variables derived from advanced satellite images at high spatial or spectral resolution, as well as fused datasets, particularly the red edge region can be used to accurately predict C:N in rangelands. Other than optical datasets, the algorithm employed largely depends on how effectively these images can predict the C:N ratio distribution. The use of the non-linear regression algorithm such as the random forest model have been used in predicting foliar biochemical properties (Ramoelo et al., 2015c, Choudhary et al., 2022). This is due to RF's ability to overcome issues of multi-collinearity, while integrating and investigating the relationship between the spectral properties in a model (Breiman, 2001a). Albeit, since the RF only provide ranks, and not remove reductant variable, feature selection methods such as the Boruta algorithm, that determine an optimal subset of variables are important (Poona and Ismail, 2013).

In this regard, this study sought to test the strength of open-access Sentinel 2, commercial PS as well as fused bands and derived vegetation indices in enhancing the C:N ratio prediction within a rangeland using the Boruta feature selection. Our objectives were; 1) to determine the trade-off between high spatial, low spectral PS and moderate spatial, high spectral Sentinel 2 data in predicting the C: N ratio in a rangeland, 2) to determine if the fusion of Sentinel 2 and PS improves the model accuracy of predicting the C:N ratio in a rangeland compared to individual sensors and 3) to determine the important variables using Sentinel 2, PS and the fused images in estimating the C: N ratio within a rangeland.

4.2. Materials and method

4.2.1 Field data collection

Field data was collected from the 28th of March to the 1st of April, 2022 under favourable conditions, and when biomass was at its peak to decouple the effect of biomass on C:N ratio (Mutanga et al., 2004a). Using a purposive sampling technique, 120 sampling points were generated at 150m apart. A 10m x 10m plot size was chosen for each sampling point, to correspond with the spatial resolution of Sentinel 2. Two subplots of 1m x 1m were randomly established in each sampling plot to capture plot variability and for clipping grass. A handheld Trimble Global Positioning System (GPS) receiver with a sub-meter accuracy was used to get the geographic co-ordinates of each sub plot. Additionally, grass samples from each subplot were clipped, their wet biomass measured with a calibrated digital scale, put in brown envelopes, and labelled for additional laboratory analysis.

4.2.2 Chemical analysis

The grass samples were taken to the laboratory and oven-dried at 65 °C for 48 h, milled, and sieved. Two milligrams of the milled powder of each sample were analysed using an elemental analyser with a combustion temperature of 950 °C and a reduction temperature of 640 °C to determine the total C and N content in percentage (g 100 g^{-1}, %). In each sample, the amount of C and N were determined synchronously. Forage C: N ratios were determined by dividing the amount of C by the amount of N in forage, based on weight (Xu et al., 2018).

4.2.3 Images acquisition and pre-processing

Planet Scope (PS) is a CubeSat satellite constellation operated by Planet Labs, Inc, and is accessible freely to researchers through a license at https://www.planet.com/. The third generation PS sensors (Super doves) was launched in 2019 with a swath width of 32.5 × 19.6 km (Kluczek et al., 2023). With about 120 satellites, the PS constellation can acquire daily images of the entire surface of the Earth. For this study, the surface reflectance product images were downloaded on the 29th of March with geometric, radiometric and atmospheric correction (Team, 2020). The PS has a 3.7m spatial resolution, 16-bit radiometric resolution, with 8 spectral bands; Coastal Blue 431 - 452 nm, Blue, 465 - 515 nm Green I, 513 - 549 nm, Green II, 547 - 585 nm Yellow, 600 - 620 nm Red, 650 - 680 nm Red-Edge, 697 - 713 nm Near Infrared, 845 - 885 nm (Kluczek et al., 2023). The PS spectrum has similar Sentinel 2 bands in 6 channels. These have a positional precision of less than 10 m RMSE and a Ground Sampling Distance (GSD) of 3–4 m at nadir (Planet Team, 2018). Two scenes were mosaicked to cover the study area and then uploaded into the Google earth engine for further analysis.

A cloud-free, radiometric and atmospherically corrected single Sentinel 2 (S2) imagery for the study area was downloaded from Google Earth Engine (Choudhary et al., 2022) from the 29th of March to the 1st of April, 2002. Sentinel 2 bands include; coastal-band 1 (443), blue-band 2 (490), green-band 3 (560), red-band 4 (665), red-edge-band 5 (705), red-edge-band 6 (740), red-edge-band 7 (783), near-infrared-band 8 (842), near-infrared-band 8A (865), water vapour-band 9 (842), shortwave infrared-band 11 (1614) and shortwave infrared-band 12 (2190) at varying spatial resolutions of 10, 20, and 60 m (Reza Pahlefi et al., 2022). However, bands 1, 9 and 10 were excluded from the analysis, since they are intended for detecting atmospheric properties and are not appropriate for analysing vegetation.

For fusion purposes, both Sentinel 2 and PS images were georeferenced in WGS 84 projection Universal Transverse Mercator (UTM) coordinate system with the same geographic coverage. Additionally, image registration, a crucial step in image processing applications (Li et al., 2022c) that involves matching different images of the same scene obtained from different angles or times, was used on the images.

4.2.4 Image fusion

Using a pixel level fusion technique, Sentinel 2 and Planetscope datasets were fused using the ENVI (version 3.1.3) software. Mngadi et al. (2021b) and Useya and Chen (2018) demonstrated that spectral information from the base image are preserved using pixel level fusion with negligible distortion and noise. In this study, the Nearest Neighbour Diffused (NND) fusion method, which is based on pixel-level fusion, was used. This method assumes that each spectral component of the high-resolution fused image is a weighted mixture of the spectra of nearby superpixels in the low-resolution spectral image (Sun et al., 2014, Ducay and Messinger, 2022). Contrary to most existing techniques (i.e., Gram–Schmidt, Brovey Transform) that treat each band separately, NND uses per-pixel spectrum processing, thereby reducing noise and minimizing bilinear interpolation (Sun et al., 2014, Ducay and Messinger, 2022). As a result, the spatial features are enhanced while spectral fidelity of the image is preserved. A total of 10 vegetation indices were derived from Sentinel 2, Planet scope and the fused image for further analysis (Table 4.1).

Table 4.1: Indices generated, their description and formulae

Indices	Description	Formulae	Reference
NDVI	Normalized difference vegetation index	$\frac{NIR - Red}{NIR + Red}$	(Hassan et al., 2019)
EVI	Enhanced vegetation index	$2.5*[\frac{NIR-Red}{(NIR+6*Red-7.5Blue+1)}]$	(Huete et al., 1999)
TVI	Triangular vegetation index	$0.5 * [120 * (NIR - Green) - 200 * (Red - Green)]$	(Cui et al., 2019)
GNDVI	Green normalized difference vegetation index	$\frac{NIR - Green}{NIR + Green}$	(Gitelson and Merzlyak, 1998)
Red edgeCl	Red edge Chlorophyll index	$\frac{NIR}{RedEdge} - 1$	(Gitelson et al., 2005)
MSRI	Modified simple ratio index	$\frac{\frac{NIR}{Red} - 1}{\sqrt{\frac{NIR}{Red} + 1}}$	(Chen, 1996)
DVI	Difference vegetation index	$NIR - Red$	(Naji, 2018)
SR	Simple ratio	$\frac{NIR}{Red}$	(Jordan, 1969)
MTVI	Modified triangular vegetation index	$1.2 * (NIR - Green) - 2.5 * (Red - Green)$	(Haboudane et al., 2004)
$NDVI_{RE}$	Red-edge normalized difference vegetation index	$\frac{NIR - Red\ Edge}{NIR + Red\ Edge}$	(Thompson et al., 2019)
MTCI	MERRIS terrestrial chlorophyll index	$\frac{NIR - Red\ Edge}{Red\ Edge - Red}$	(Dash et al., 2010)

4.3 Model development and statistical analysis

The random forest (RF) ensemble machine learning algorithm builds multiple regression trees and averages the outcome to predict a response variable (measured C: N ratio) through a set of predictor variables. The random forest algorithm (RF) is a regression method that is based on a large matrix of decision trees (Breiman, 2001a), where each tree is dependent on a random vector and every vector in the forest is independent and has an identical distribution (Biau and Devroye, 2010). The algorithm randomly fits many decision trees on different sub-samples of the dataset using a bagging (bootstrap) operation and then uses the averaging strategy to increase predicted accuracy and reduce over-fitting (Tariq et al., 2022, Odindi et al., 2014). RF utilizes two parameters, namely *ntree*, which makes use of several subsets of decision trees, and *mtry*, which takes into account the predictor variables at each tree node to improve model optimization results (Breiman, 2001b, Wei et al., 2023). The ideal *ntree* and *mtry* values for the best prediction model are determined by the smallest cross-validation error (Breiman, 2001a)**.** In this study the optimal *ntree* and *mtree* values for PS were determined to be 300 and 14, respectively, while for Sentinel 2 and the fused image, the *ntree* and *mtree* were identified as 200 and 17, and 300 and 15, respectively. To validate the model and determine the variable importance, 30 percent, as recommended by Adelabu et al. (2015) of the samples or Out-Of-Bag (OOB) samples that were not utilized in the bootstrap samples were used.

4.3.1 Optimal Predictor Variable Selection

Most predictive models require a minimal number of the most influential variables to be computed, due to multicollinearity between variables. The Boruta feature selection was used in this study for optimal variables selection in predicting the C:N ratio spatial distribution (Poona and Ismail, 2013). Boruta algorithm, a RF wrapper assesses significant variables by assembling a collection of equivalent artificially added "shadow" variables that are randomly selected from the dataset (Breiman, 2001a, Poona and Ismail, 2014). Boruta calculates and iteratively compares Z-scores between each variable and the shadow variable using this expanded dataset. The next step in determining the relevance of a variable is to compare it to its counterpart in the randomized dataset (Kursa, 2012). Until variables are categorized as Confirmed, Rejected, or Tentative, several random forest models are run iteratively (Poona and Ismail, 2013).

4.4 Results

Based on the descriptive statistics, the minimum and maximum values of the measured C:N ratio within the rangeland were 14.21 and 40 with a standard deviation of 5.21 and a mean of 22.

4.4.1 Feature selection

Figure 4.1 a, b and c show the Boruta variable selection graph for Planetscope, Sentinel 2 and the fused variables. The green box and whisker plots indicate the selected variables; the red bars indicate rejected variables and the blue boxplot represents the Z- score of the shadow variable. The graph demonstrates that green variables are more significant than shadow variables, which are represented by blue lines, and have higher values.

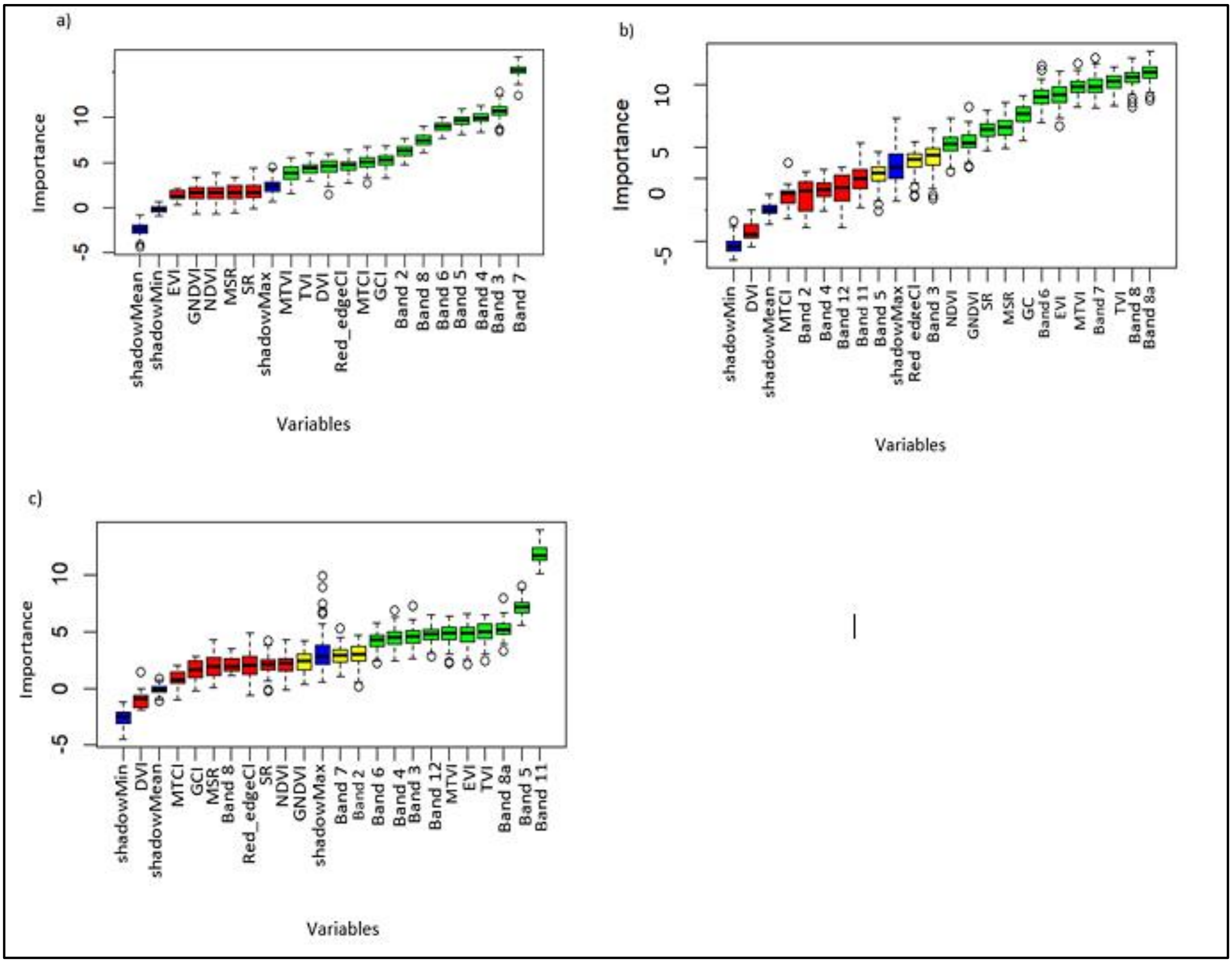

Figure 4.1: Variable selection by Boruta algorithm, in a) Planetscope, b) Sentinel 2, and c) fused datasets – green bars indicate the selected variables, the red bars indicate rejected variables and the yellows bars indicate tentative features.

Figure 4.2 shows the optimal variables in modelling the C:N ratio using Boruta algorithm, and their ranking in terms of importance. As shown in Figure 4.2a, band 7 (red edge band), and band 3 (green) were the most influential Planetscope variables. In figure 4.2b, bands 7 and 6 (red edge) and band 8 (near-infrared) significantly contributed to the model performance using Sentinel 2 in predicting C:N ratio in the study area. Lastly, results from the Boruta algorithm show that bands 8a,6,7, and 3 (NIR, Red edge bands and green) were the optimal variables using the fused data in predicting the C:N ratio. According to the results, the bands perform better than the vegetation indices across all models.

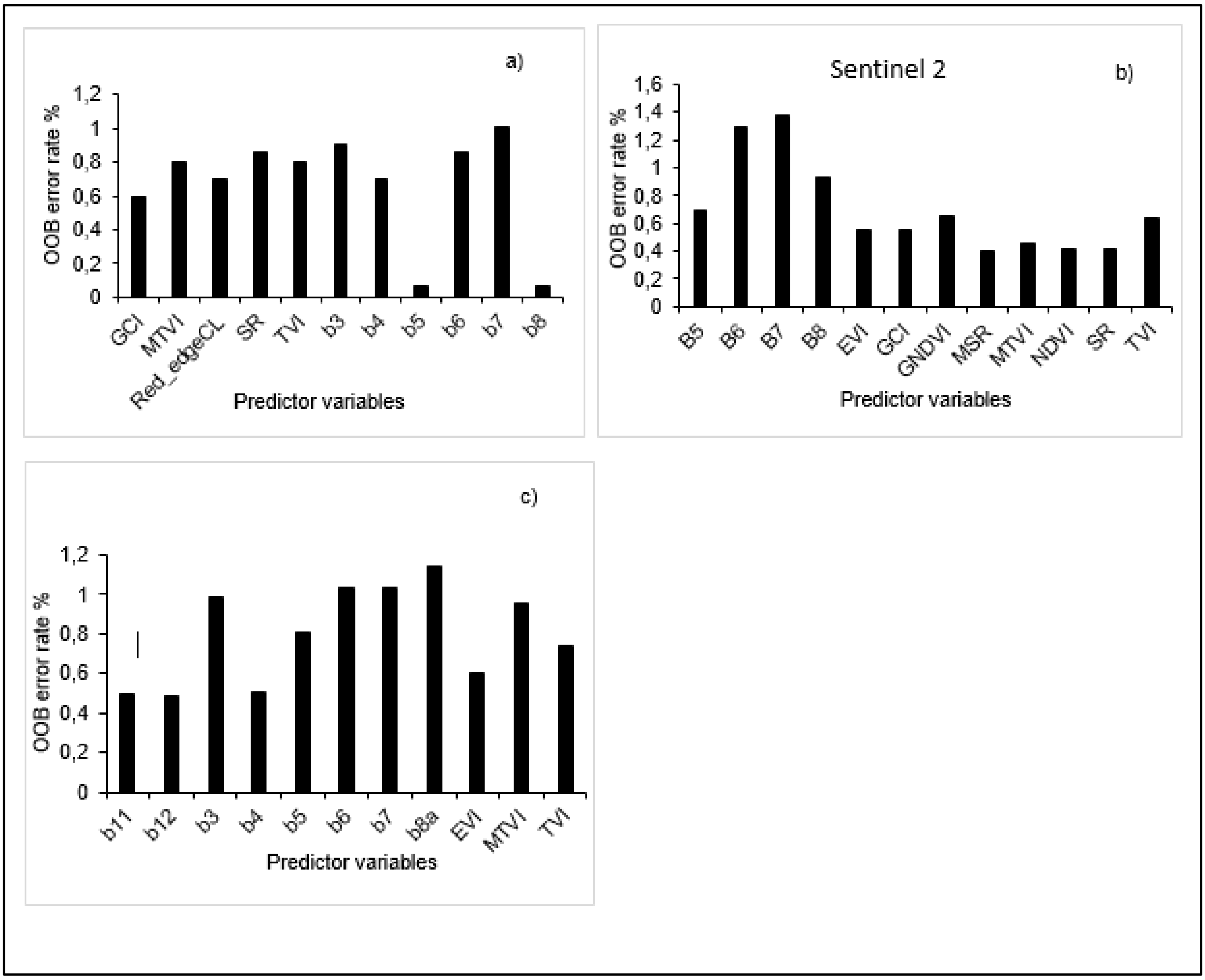

Figure 4.2: The measure of optimal variables' importance in predicting C:N ratio using a) Planetscope, b) Sentinel 2 MSI, c) fused Planetscope with Sentinel 2. An increasing OOB error rate indicate higher variable importance.

4.4.2 Evaluation and performance of the models

4.4.2.1 The C:N ratio estimation

Table 4.2 shows the C:N ratio estimates and predictive model performance. The C:N ratio estimates of PS for both calibration and validation datasets were R^2 of 0.75 to 0.60, RMSE of 2.88 to 3.40 and mean of 22.88 to 23.23. The S2 gave a better model accuracy with R^2 of 0.80 to 0.70, RMSE of 2.43 to 2.82 and mean of 22.8 to 23.04 using both the calibration and validation datasets. The fusion of the optimal spectral predictor variables from S2 and PS produced the best results with R^2 of 0.84 to 0.79 and RMSE of 2.13 to 2.36 and mean of 23.17 to 22.08 for calibration and validation datasets.

Table 4.2: The estimation accuracies of the C:N ratio derived using Planetscope, Sentinel 2 and fusion of Sentinel 2 and Planetscope derived spectral data.

Image	Prediction dataset	Mean	R^2	RMSE	r
Planetscope	Calibration	22.88	0.75	2.88	0.84
	Validation	23.23	0.60	3.40	0.76
Sentinel 2	Calibration	22.80	0.80	2.43	0.90
	Validation	23.04	0.70	2.82	0.83
Fused data	Calibration	23.17	0.84	2.13	0.92
	Validation	22.08	0.79	2.36	0.90

Figure 4.3 shows the relationship between the measured and estimated C:N ratio using spectral variables derived from Planetscope, Sentinel 2 and fused Planetscope and Sentinel imagery. The results demonstrate that the predicted C:N ratio for Planetscope, Sentinel 2 and fused datasets in the study area are strongly correlated with the measured C:N ratio, with a coefficient value of 0.76, 0.83 and 0.90, respectively.

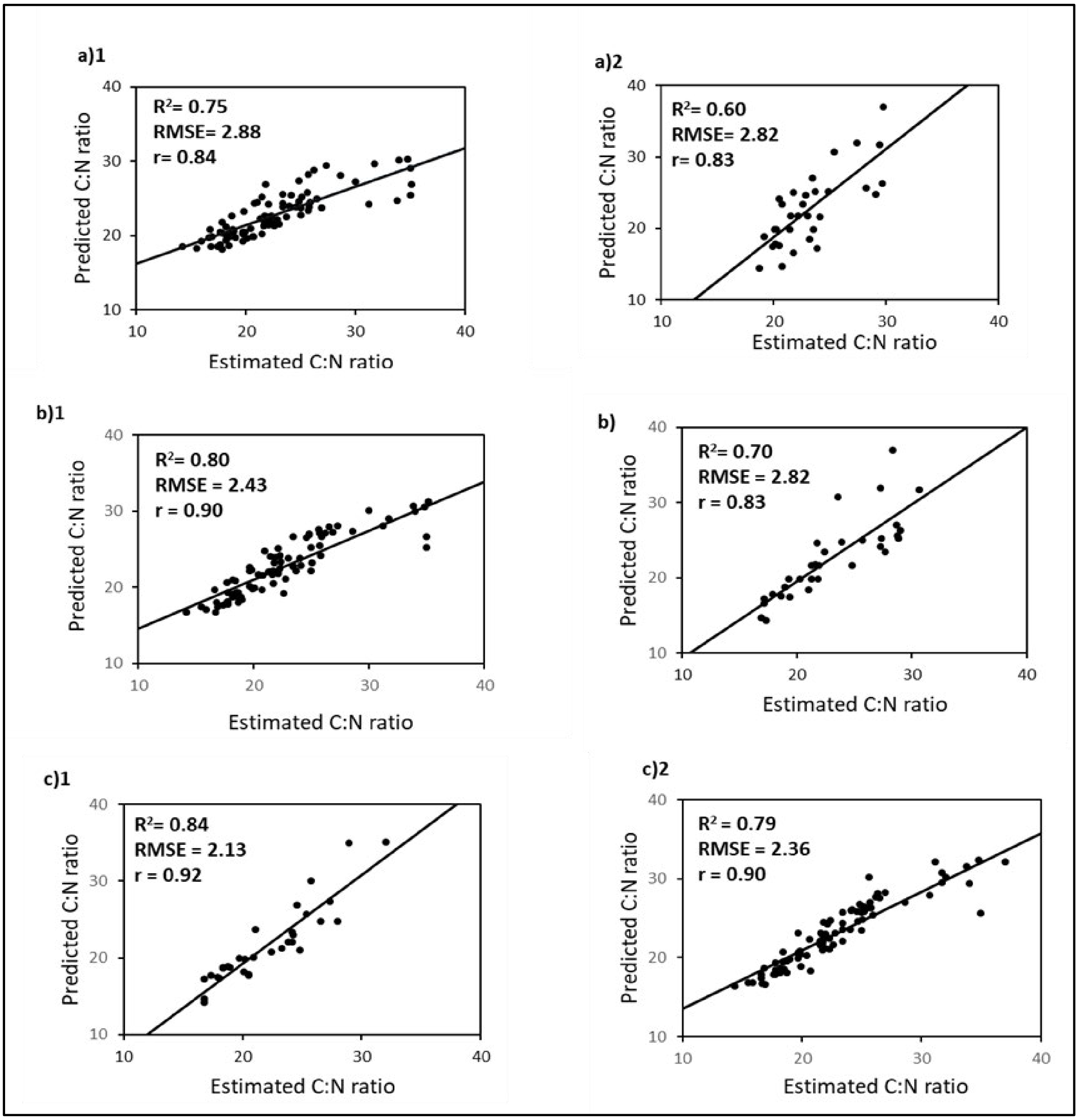

Figure 4.3: Relationship between the measured versus predicted C:N ratio derived using the calibration(1) and validation(2) datasets generated from Planet scope(a), Sentinel 2(b), and fused datasets (c).

4.4.3 The spatial distribution of the C:N ratio in the rangeland

The spatial distribution of the C:N ratio was estimated based on the optimised RF regression. The C:N ratio for Planetscope ranged between 17.7 to 31.5 (Fig 4.4a), whereas Sentinel 2 ranged between 16.4 to 31.8 (Fig 4.4b), and 16.3 to 33 for the fused image (Fig 4.4c). The distribution of foliar C:N ratio varies spatially, with areas that are poorly vegetated (poor grassland management or heavily grazed) showing a higher concentration of C:N ratio, while lower C: N ratio indicates densely vegetated areas with good forage quality (depending on the herbivore). The C:N ratio map indicates the health status of rangeland in the study area. As a result, the final map presents the possibility of relating forage C:N ratio variability to range conditions.

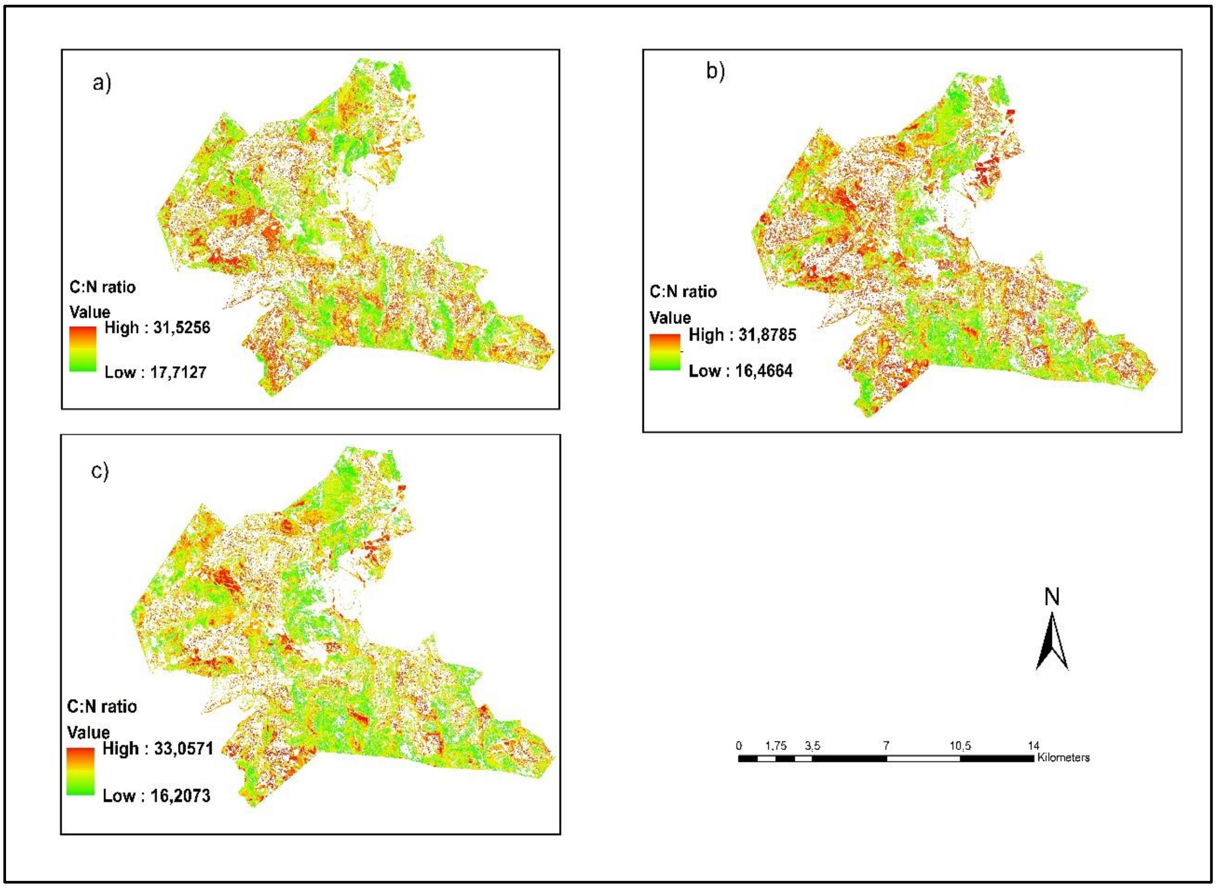

Figure 4.4: Spatial distribution of predicted C:N ratio generated using (a) Planetscope datasets, (b) Sentinel 2 datasets and (c) fused image datasets.

4.5 Discussion

This study investigated the value of fusing spectral metrics derived from high spatial (PS) and high spectral (Sentinel-2) imagery to enhance the monitoring of C:N ratio within a heterogeneous rangeland using the random forest algorithm. The study revealed that integrating optical sensors improved the prediction accuracy of the C:N ratio within the rangeland. Furthermore, results from this study show that enhancing the spatial resolution of S2 with PS data improved the C:N ratio estimation with accuracies increasing from R^2 = 0.75, 0.80 to 0.84 for PS, S2 and the fused datasets, respectively. These findings are similar to other studies that fused different sensors for vegetation monitoring (Gašparović et al., 2018, Tewes et al., 2015, Xu et al., 2023). The study by Gašparović et al. (2018) for instance reported that the fusion of S2 and PS produced higher accuracy for the detection and monitoring of vegetation compared to individual sensors in Croatia. In South Africa, Tewes et al. (2015) found that the fusion of MODIS 250 m resolution and RapidEye 5 m resolution images produced superior accuracy and detailed information on vegetation dynamics that would not have been captured by the sensors alone within a heterogeneous rangeland. The high prediction of the fused data in our study can be attributed to the complementarity of the S2's rich spectral information with the high spatial resolution from Planet scope. For example, the spectral reflectance is sensitive to chlorophyll content as well as the leaf internal structure, whereas the spatial resolution offers detailed information critical for discriminating plant characteristics required for well- informed vegetation management (Gašparović et al., 2018). Optical sensors are known to suffer from saturation issues, clouding, and soil background effects, which may impede the estimation of foliar nutrients in grasslands (Jennewein et al., 2022, dos Santos et al., 2022). However, the fusion of optical data can reduce these constraints and provide robust information that enhances the estimation of the foliar nutrients (Schmidt et al., 2012, Gašparović et al., 2018)**.** Also, the non –linear model technique (RF) contributed to the model accuracy due to its ability to handle highly correlated predictors. A similar performance of the RF modelling approaches has been documented in foliar nutrient studies. For example, in China, Gao et al. (2020a) predicted the C:N in a rangeland using hyperspectral data, with RF and a support vector machine(SV). They stated that the RF performed better than the SV, and similar to our study was able to predict > 80% in the spatial distribution of the C:N ratio. Evaluating different algorithms, Osco et al. (2020) discovered the dominance of the RF over the artificial neural network, decision tree, lasso regression, k- Nearest Neighbour and support vector machine in predicting micro and micronutrients levels in Valencia orange leaf using field hyperspectral data. Kluczek et al.

(2023) highlighted the superior performance of RF over deep learning methods (convolutional neural network classifiers) in mapping vegetation from medium-resolution satellite imagery (such as Sentinel-2), where spectral features play a dominant role, especially in complex and diverse plant species.

The results show that across all models, the spectral bands (red edge, red, green and NIR) produced higher accuracies compared to derived vegetation indices for estimating the C:N ratio. The result in this study is contrary to Minaei et al. (2022) who reported that spectral indices outperformed bands in predicting foliar nutrients. Vegetation indices computed from different spectral bands can deal with the effects of soil background, atmospheric influence and angle of the sensor (Ghimire et al., 2020, Sibanda et al., 2017a). However, the results in this study is similar to Arogoundade et al. (2023d), Sibanda et al. (2021) and Masenyama et al. (2023) who reported the optimal performance of bands compared to VI in mapping grassland nutrients within the study area. The higher accuracy of the bands in this study can be attributed to the grass covering much of the ground surface, thereby limiting the background influence on spectra.

By analysing the models' performance separately based on PS and S2, we could better understand the relative contributions of each satellite to the fused data**.** The results show that the near-infrared, red edge and green bands were influential in the models. S2 contains three red edge and NIR regions that have been demonstrated to provide valuable information in plant nutrient detection and monitoring (Abdullah et al., 2019, Majasalmi and Rautiainen, 2016). Furthermore, the NIR and red edge regions have been associated with nitrogen and carbon-based constituents (cellulose, lignin, and starch) (He et al., 2006a, Xu et al., 2018, Gao et al., 2020a), hence its optimal influence in estimating rangeland C:N ratio in this study. In China, Gao et al. (2020b) using Sentinel 2 imagery, illustrated that bands 9 (NIR) and 12 (SWIR) and vegetation indices derived from the red edge and NIR were the most relevant for modelling the N:P ratio in the Alpine grasslands. The influence of the red edge bands in the prediction of C:N ratio could be attributed to the region’s high sensitivity to subtle variations of foliar properties such as chlorophyll, protein, carbon-based constituents, leaf area index and biomass, that are correlated C:N ratio a canopy level (Gao et al., 2020a). In different studies, Durante et al. (2014), and Gao et al. (2020a) illustrated that the red edge and NIR were influential predictor variables in their studies on grasslands. Additionally, the NIR region can provide valuable information on plant health and productivity, as it can detects plant’s leaf surface and internal structures (Zahir et al., 2022). The influence of the green band in the visible region of the electromagnetic spectrum in predicting the C:N ratio was also noted in this study. Similar results were obtained by Schlemmer et al. (2013) and Vasudeva et al. (2021) who reported that the green region is highly sensitive to changes in nitrogen, chlorophyll and carbon based constituents. The green region, which approximately reflects at 550nm, is strongly linked to chlorophyll (an important pigment in photosynthesis) due to the high reflection of chlorophyll a and chlorophyll b in the light region (Zahir et al., 2022). Schlemmer et al. (2013), illustrated that the green or red-edge spectral areas, can avoid saturation and maintain the high sensitivity to changes in plant stress as evidenced by changes in chlorophyll concentration, unlike the red absorption region where absorption saturates at moderate to high chlorophyll concentrations (Hatfield et al., 2008, Gitelson, 2011). This could possibly explain the importance of the visible, NIR and red-edge based spectral variables in determining the C:N ratio within the rangeland.

Furthermore, unlike low or medium spatial sensors, high spatial resolution sensors like PS have proven to be important in foliar nutrient prediction due to their ability to detect finer details in heterogeneous landscape with varying species (Sibanda et al., 2017a, Pereira et al., 2022). PS contribution can be attributed to the 3.7m pixel size which can detect subtle variation (Ghildiyal and Cardoso, 2020), and provide detailed information in the estimation of C:N ratio in the rangeland at a local scale. This finding is supported by Tarantino et al. (2016) and Räsänen and Virtanen (2019) who found that the pixel size enhanced the prediction accuracy in mapping plants in spatially heterogonous landscapes. On the other hand, Rossi et al. (2022) reported that high spatial resolution might enhance within-species variation and increase noise, making it challenging to establish a significant spectral diversity–biodiversity relationship. The prediction of the C:N ratio was substantially improved by the application of the NND pixel level fusion which kept the original spectral information, while eliminating image distortion and noise during processing. Li et al. (2021a), and Zhang et al. (2018) for example, reported that NND produced better quality images compared to other fusion approaches such as Wavelet Resolution Merge, Gram Schmidt, Bovey, and Principal Component due to their high signal-to-noise ratio.

In this study, the spectral properties of Sentinel 2 were more relevant than the high spatial resolution of Planetscope in predicting the C:N ratio. The lower accuracy of PS in predicting the C:N ratio can be attributed to the lower spectral and radiometric resolution, and the impacts of undulating terrain on surface reflectance values (Yu et al., 2020b). A study by Mutanga et al. (2016) reported that sensors with low spectral resolution fail to take advantage of the presence of a large number of distinct spectral wavebands that can identify absorption features. Tu et al. (2022) also evaluated the surface reflectance of Sentinel2 against PS across different types of surface units and found that the uncertainty and absolute average accuracy were 7% and 6% for Planet scope Superdove, and 4% and 0% for Sentinel 2, respectively. Furthermore, the yellow, red, red edge and NIR bands had lower absolute accuracy of 8% compared to the blue, coastal blue, green1 and green II with 3% absolute reflectance accuracy. This might have influenced the accuracy of the PS model in our study, as the regions sensitive to vegetation monitoring lie within the red and near-infrared section of the electromagnetic spectrum. Hence, this study supports the notion that more spectral bands, especially the red edge and near infrared are important in predicting foliar biochemicals in plants.

The spatial distribution of the C:N ratio in the study area is demonstrated in figure 6. From the upper to lower boundaries, the figures show great consistency, with a lower C:N ratio in densely vegetated areas compared to moderately or non-vegetated areas. Similarly, Phillips et al. (2006) reported that fertilized *A. desertorum* had a lower C:N ratio (greater forage quality) than severely and moderately grazed mixed-grass prairie (25.8 ± 1.4, 28.8 ± 2.5, and 30.6 ± 4.5, respectively). This variability can be attributed to topographic variables and climatic changes which have been reported to influence foliar nutrient distribution within vegetation (Frank, 2008). Additionally, the study by Phillips et al. (2006) and Berri (2007) illustrated that the choice of grassland management practices (grazing, burning, and fertilization), as well as the species of grass, can have an impact on variation in C:N spatial distribution because these practices affect the biochemical properties of the grass.

Generally, this study concludes that PS's high spatial resolution offers detailed information that was complementary to S2, and improved the C:N ratio mapping and prediction. This study has demonstrated the ability of NND, a pixel-level image fusion approach to effectively combine optical sensors for C:N ratio in rangeland. However, further studies are required to explore the integration of different data sources in predicting foliar nutrients and optimal algorithms for predicting foliar nutrients based on multiple data sources. Also, future research should investigate the use of hyperspectral data due to its multiple bands in estimating the C:N ratio at local scale.

4.6 Conclusion

This study examined the trade-off and fusion between high spatial and spectral resolution sensors in enhancing the prediction of C:N ratio within a communal rangeland in KwaZulu-Natal, South Africa. Based on the outcomes of this study:

- Results from this study illustrated that the C:N ratio was best estimated using datasets derived from fusing PS and S2 with an accuracy of R^2 of 0.84, compared to standalone datasets from S2 and Planet scope with an accuracy of 0.80 and 0.75, respectively, within the rangeland.
- Across all the models (Plant scope, Sentinel2 and the fused datasets) the bands of each models had better accuracies compared to the vegetation indices.
- The red edge and green bands were the most influential bands using Planetscope scope, while the red edge and near infrared bands in Sentinel 2 performed better. In the fused dataset, the red edge, near infrared and green bands were the optimal variables.
- Fusing the images provided detailed information on the spatial nutrient variability of the rangeland at a local scale. The information from this study can serve as a decision support tool for rangeland managers and policymakers in the sustainable management of rangelands.
- The results in this study show that future prediction of rangeland health and mapping can benefit from open source S2 compared to commercial sensors such as PS, especially in poor and data scarce regions. Furthermore, the spectral resolution was more important than spatial resolution in predicting foliar C:N ratio in this study.

Chapter Five: A multi-source data approach to mapping C:N biochemical ratios within a heterogeneous rangeland.

Adeola Arogundade*, Onisimo Mutanga, John Odindi, and Rowan Naicker

Abstract:

Livestock distribution and grazing behaviour are often determined by forage quality within rangelands. However, rangeland have been increasingly subjected to both anthropogenic and climatic threats, which has resulted in their degradation. Thus, to ensure the sustainable management, there has been renewed effort to enhance the understanding of forage quality. Advancement in sensor technology and machine learning algorithms offer great potential in mapping the C:N ratio in heterogeneous grassland at a local scale. This is because high resolution sensors can capture the inherent variations in foliar nutrients in rangelands with diverse grass species. Nonetheless, whereas advances in sensor technology hold great potential for mapping the C:N ratio, the spectral, spatial and temporal resolutions of individual sensors, as well as their associated cost, can limit their effectiveness. The fusion of optical images from different satellite sensors such Planetscope and Sentinel 2 can produce a high-resolution image by taking advantage of their spatial, spectral and radiometric resolutions. In spite of this, both environmental and climatic variables influence foliar nutrient distribution through the relative influence they have on grass productivity, health, and species diversity. In this regard, we explored an alternative framework for estimating the C:N ratio using image fusion and multi-source data. Using the random forest algorithm, we compared the performance of Sentinel-2 and Planetscope image fusion, as well as the integration of topo-climatic variables in predicting the C:N ratio within a diverse tropical rangeland. Our results indicate that the integration of fused multispectral imagery and topo-climatic variables (R^2 = 0.82 and RMSE = 2.14) outperformed the use of fused datasets alone (R^2 = 0.78 and RMSE = 2.39). The most influential variables in predicting the C:N ratio were the: red edge (748 and 793 nm) and near infrared (900 nm) bands, wind effect, topographic wetness index, and the sky view factor. The outcomes of this study provide an alternative framework for rangeland managers to not only monitor, but also comprehend nutrient variability and load capacity across diverse ecological gradients. The findings of this study can be used to facilitate sustainable rangeland management within the vulnerable and sensitive rangeland ecosystems.

Keywords: C:N ratio, Sentinel 2, topo-climatic variables, rangeland management, machine learning

5.1 1ntroduction

In Southern Africa, rangelands play a crucial role in the livelihoods of surrounding rural communities (Mohajan, 2022). In addition to offering essential climatic and biophysical ecosystem services, rangelands contribute towards the strengthening of rural economies by providing free-range feed for livestock (Mureithi et al., 2016, Cho et al., 2023). As a result, the health of rangelands has become intricately intertwined with the well-being and livelihoods of local communities (Mureithi et al., 2016, Cho et al., 2023). Despite this relationship, unsustainable agricultural activities, such as overgrazing, coupled with the impacts of a changing climate have placed tremendous strain on neighbouring rangelands (Cibils et al., 2023, Shaumarov et al., 2012). This has affected the quality and composition of grass species as well as plant productivity, jeopardizing their long-term sustainability (Timpong-Jones et al., 2023a). Consequently, their diminished grazing-feed quality as well as reduced carrying capacity have created additional challenges for local farmers (Angerer et al., 2023). Hence, there has been a growing body of research (Mutanga, 2004, Pullanagari et al., 2016, Retallack et al., 2023) aimed at enhancing our understanding of rangeland health. Therefore, it has become imperative to provide more accurate assessments of rangeland condition to facilitate effective managements of grazing land.

In rangeland health management, foliar biochemicals, such as Carbon (C) and Nitrogen (N) represent key determinants of forage health, development and productivity (Liu et al., 2022b, Raines, 2011). Essentially, N serves as a major component of proteins and significantly influences plant productivity, while C provides the primary building blocks necessary for plant tissues (Mu and Chen, 2021). Therefore, N availability is documented to govern the photosynthetic process, which controls plant physiology development and carbon production (McAllister et al., 2012).In this regard, any reduction in nitrogen uptake and storage can significantly impact the rate of plant carbon fixation (Nunes-Nesi et al., 2010). Consequently, the relative amount of C in relation to N (C:N ratio) serves as an indicator of nutrient limitation in plants as well as a measure of their ability to utilize these nutrients to sustain optimal productivity (Seeber et al., 2022). In rangelands, the C:N ratio not only influences soil microbial populations, but also represents a functional trait indicating the quality of forage resources within the landscape (Gao et al., 2020a, Hendrickson et al., 2021, Durante et al., 2014). Literature suggests that the C:N ratio value for high quality forage (low C:N ratio – i.e., more nitrogen in the ratio) ranges from 24 to 30, whereas poor quality forage (high C:N ratio

– i.e., less nitrogen in the ratio) have values >30 (Berri, 2007, Phillips et al., 2006, Gao et al., 2020a). For instance, in the Northern Great Plains rangelands, Phillips et al. (2006) found high-quality forage (a lower C:N ratio of 23 ± 4.4), in fertilized grasses, whereas poor-quality forage have higher C:N ratio of 31.3 ± 5.5. Also, a study by Beeri et al. (2007) indicate that grazing animals in northern mixed-grass prairie require a low C:N ratio (less than 36), which is characterized by a high protein composition. Therefore, the C:N ratio has been found to function as a representative indicator of rangeland health. Thus, to gain a deeper comprehension of livestock grazing patterns as well as enhance rangeland decision-making frameworks, accurate and timely assessments of the spatial distribution of C:N ratios in rangelands is necessary.

The adoption of remotely sensed data for monitoring rangeland nutrients has been widely recognized as a highly effective and cheaper alternative to the traditional field and laboratory techniques (Roth et al., 2023, Sharifi and Felegari, 2023). This is due to the ability of remotely sensed data to provide spatially explicit assessments on plant nutrients, such as chlorophyll, nitrogen, starch, lignin, and cellulose across diverse landscapes in near-real time (Ali et al., 2022, Retallack et al., 2023). Modern technical advancements in sensor capabilities have led to the introduction of superior multispectral sensors with improved spectral and spatial configurations (Zhang et al., 2023, Sharifi, 2020). For instance, both 13-band Sentinel-2 MSI (with a 10m spatial resolution and 5-day revisit period) (Ramoelo et al., 2015a, Sadeh et al., 2021) and 8-band Planet-scope (with a 3.5m spatial resolution, 1-day revisit, and a 431-85 nm spectral range) (Gašparović et al., 2023) have provided unprecedented opportunities for the detection of foliar nutrient detection in rangelands. However, although useful, the practicality of these sensors can be limited by their individual spatial, temporal, and spectral shortcomings (Sadeh et al., 2021). For example, the spatial and temporal configuration of Sentinel-2 limits its practical application for monitoring rapid changes within a small, localized environment, while the poor radiometric resolution of Planet-Scope inhibits its vegetation monitoring accuracy (Amankulova et al., 2023, Arogoundade et al., 2023a). To mitigate these limitations, the fusion of different sensors has been shown to enhance plant biochemical and biophysical mapping accuracy (Sadeh et al., 2021, Li et al., 2019). For example, both Sadeh et al. (2021) and Li et al. (2019) successfully fused Sentinel-2 and Planet-Scope data, to create a high spatiotemporal image with improved spectral quality to estimate wheat productivity (leaf area index).

Furthermore, studies (Chabalala et al., 2020b, Sibanda et al., 2017a) have highlighted the need to alleviate the environmental background interferences in model estimates. As a result, vegetation indices (VI) generated from the red edge bands have proven effective in contending with background interferences and enhancing the foliar biochemical estimation (Zhang et al., 2022, Mashiane et al., 2023). For instance, Mutanga and Skidmore (2007) and Tian et al. (2011) demonstrated the superiority of red-edge bands and associated vegetation indices in estimating and mapping foliar nutrients. However, such studies were based on hyperspectral image data, which comes with various shortcomings that include high cost and are not readily available (Sibanda et al., 2020, Gao et al., 2020a, Xu et al., 2018, Lihong et al., 2006).

Nevertheless, topographic variables (e.g., topographic wetness index, slope, aspect, elevation, soil moisture and curvature) and climatic factors (precipitation and temperature) play a crucial role in shaping the distribution of foliar nutrients through their relative influence on grass productivity, health and species heterogeneity (Adjorlolo et al., 2015, Sanaei et al., 2023, Chadaeva and Pshegusov, 2022). For instance, Ramoelo et al. (2013) noted that environmental variables including temperature, geology, soil, and distance to river are influential in the spatial distribution of the N:P ratio in the Lowveld savannah of South Africa.. Furthermore, Yu et al. (2017b), He et al. (2006b) and Arogoundade et al. (2023d) noted the ecological impact including the regulatory function of foliar nutrients such as C:N ratio in global climate change (Kunz et al., 1995) and potential contribution to forage quality. However, there is limited understanding on the specific climatic and topographic factors influencing the spatial distribution of the C:N ratio, especially from a remote sensing perspective within the unique and biodiverse rangeland of KwaZulu-Natal. Therefore, understanding the spatial variability of the C:N ratio in grasslands in response to topographic and climatic factors is increasingly becoming necessary, especially in developing countries.

To adequately map foliar biochemicals, studies such as (Knox et al., 2012, Ramoelo et al., 2013, Ramoelo and Cho, 2018) have highlighted the need to integrate site-specific topo-climatic data with optical imagery to improve the accuracy of models in foliar nutrient estimation. Despite this, existing studies on predicting C:N ratios within rangelands have primarily focused on optical sensing methods (Arogoundade et al., 2023d, Arogoundade et al., 2023a, Beeri et al., 2007, Phillips et al., 2006, Gao et al., 2020a). For instance, Phillips et al. (2006) utilized Landsat 5 (RMSE = 3.1) and ASTER (RMSE = 1.5) multispectral data to measure C:N ratio variability, while, Gao et al. (2020a) used hyperspectral data and the random forest algorithm to model foliar C:N ratios in a Tibetan rangeland with an accuracy of 85% to

92%. In South African rangelands, Arogoundade et al. (2023a) and Arogoundade et al. (2023d) used multispectral imagery to retrieve forage C:N ratios. Nonetheless, although Arogoundade et al. (2023a) investigated the utility of fused Sentinel-2 and Planet-Scope multispectral imagery in estimating C:N ratios, they did not consider the influence of topo-climatic features. Thus, to the best of our knowledge, no study has explored the influence of topo-climatic variables and multi-sensor image fusion to map C:N ratios within heterogeneous rangeland. Subsequently, this study sought to develop a framework to map foliar C:N ratios within a tropical heterogeneous rangeland using fused high spatio-temporal multispectral imagery and ancillary topo-climatic datasets.

5.2. Materials and methods

5.2.1 Field data and collection

Data was collected in the study area between the 28th of March and the 1st of April, 2022, coinciding with peak biomass growth to mitigate the effect of biomass on the C:N ratio (Timothy et al., 2016). Employing a purposive sampling approach (Mkungo et al., 2023), we established a total of 120, 10m x 10m quadrants at 150m apart. Each quadrant comprised of two randomly selected 1m x 1m sub-quadrants that were used to obtain grass clippings. The cut grass samples from each subplot were weighed, and labelled for laboratory analysis. The geographic coordinates of each sub-plot's centre were recorded using a portable Trimble Global Positioning System (GPS) receiver with sub-meter precision.

5.2.2 Chemical analysis

The grass samples were processed in the lab (oven drying at 65 °C for 48 hours, crushed, and sieved). Using an elemental analyser with a combustion and reduction temperature of 950 °C and 640 °C respectively, 2 milligrams of the milled powder of each sample were analysed for C and N content in percentage (100 g-1) (Xu et al., 2018, Gao et al., 2020a). The amounts of C and N in each sample were calculated simultaneously by dividing the forage's C content by its N content, based on weight (Gao et al., 2020a).

5.2.3. Image and data acquisition

A single image of Sentinel 2 multispectral sensor launched by the European Space Agency's (ESA) was downloaded from the Google Earth Engine (GEE) catalogue for the period between the 28th of March and the 1st of April 2022. Sentinel 2 consists of two satellites (2A and 2B), at a distance of 180° apart with a 290km swath width (Main-Knorn et al., 2017). Sentinel 2A has 13 spectral bands detailed in Table 6.1, with spatial resolutions ranging from 10m, 20m and 60m and a 5-day return interval cycle designed for timely and continuous monitoring of vegetation at landscape scales (Munyati et al., 2020). Given its expansive coverage and open accessibility, Sentinel-2 data has been instrumental in rangeland monitoring and management (Sibanda et al., 2015, Sibanda et al., 2021). Notably, the incorporation of red edge bands in Sentinel 2 have facilitated the detection of minute variations in foliar nutrients, such as the C:N ratio (Arogoundade et al., 2023c). The Sentinel 2 imagery for the study area was downloaded as a single image with less than 5% cloud coverage, that had been orthorectified, atmospherically and geometrically corrected using the GEE (Choudhary et al., 2022). For this study, bands 1,9, and 10, primarily used for atmospheric analysis, were excluded, as they do not impact foliar nutrient estimation (Masenyama et al., 2023).

In addition to the Sentinel-2 imagery, two pre-processed Superdove Planetscope (431 -885 nm) images, with a spatial resolution of 3.7m were downloaded from **https://www.planet.com/** on the 29th of March, 2022. These images were mosaicked into a single file, and clipped to the boundary of the study area using the ENVI software (Xie et al., 2003). Launched in 2019, Superdove Planetscope is equipped with eight very high spatial resolution (3.7m) bands (Table 1) and a swath width of 32.5 × 19.6 km (Farmonov et al., 2023). Following the method applied by Farmonov et al. (2023), band 1 (coastal blue) was omitted from consideration in this study due to its negligible contribution to vegetation monitoring.

Thereafter, both images (Sentinel 2 and Planetscope MSI) were georeferenced to the Universal Transverse Mercator (UTM) coordinate system (Bright et al., 2009). Additionally, using the ENVI software, image registration process was executed to ensure alignment between the two images, thereby minimizing errors within the image processing techniques (Jin, 2017). In this study, emphasis was placed on exploring vegetation indices that have demonstrated efficacy in explaining foliar nutrients variation and distribution (Arogoundade et al., 2023d, Sibanda et al., 2021, Zhao et al., 2018). In addition to the conventional Normalized difference vegetation index (NDVI), and simple ratio (SR), various other NDVIs and SRs were derived using the combination of different red edge bands (red edge I, red edge 2, and red edge 3) from the fused Sentinel 2 dataset. These vegetation indices were considered based on their performance in previous studies in estimating foliar N, carbon-based constituents (lignin, starch and cellulose), and chlorophyll in vegetation (Ramoelo and Cho, 2018, Adjorlolo et al., 2014, Vasudeva et al., 2021).

Table 5.1. Spectral range of the Sentinel 2 and Planetscope MSI.

Sentinel 2 MSI			Planetscope MSI		
Band	Wavelength(nm)	Designation	Band	Wavelength(nm)	Designation
Band 1	433-453	Coastal aerosol	Band 1	431 - 452	Coastal Blue
Band 2	458-523	Blue	Band 2	465 - 515	Blue
Band 3	543-578	Green	Band 3	513 - 549	Green I
Band 4	650-680	Red	Band 4	547 - 585	Green I1
Band 5	698-713	Red edge 1	Band 5	600 - 620	Yellow
Band 6	733-748	Red edge 2	Band 6	650 - 680	Red
Band 7	773-793	Red edge 3	Band 7	697 - 713	Red-Edge
Band 8	785-900	Near infrared 1	Band 8	845 - 885	Near Infrared
Band 8A	855-875	Near infrared 2			
Band 9	935-955	Water vapour			
Band 11	1565–1655	Shortwave 1			
Band 12	2100-2280	Shortwave2			

5.2.4 Image fusion

In this study, a pixel-level fusion approach was employed within the ENVI software environment (version 3.1.3) to fuse the Sentinel 2 and Planet scope datasets. Specifically, the Nearest Neighbour Diffusion (NNDiffuse) technique, a pixel-based approach that has proved successful in fusing multispectral data, was used (Ducay and Messinger, 2022, Arogoundade et al., 2023a). The performance of the NNDiffuse power can be attributed to speed, radiometric accuracy (lower spectral distortions), and the lack of training data required (Ducay and Messinger, 2022) as well as the ability to improve image spatial features while maintaining its spectral fidelity. Eight vegetation indices were generated from the fused datasets. These vegetation indices were computed based on the spectral arrangement of Sentinel 2 multispectral data, incorporating various configurations of the red-edge bands (Table 5.2).

5.2.5 Acquisition and processing of environmental factors

Topographic variables were generated from a 30m x 30m Shuttle radar topography mission (SRTM) using SAGA GIS (2.3.2) and ArcGIS 10.6 software. The topographic variables were grouped into three classes, i) local (elevation, aspect and curvature) ii) non - local (openness, flow accumulation and catchment area), and iii) mixed topographical variables (slope length factor, topographic wetness index) (Li et al., 2018). The local metrics analyse the geometry of a specific site on the land surface, while the non-local metrics represents the relative locations of selected locations. The mixed topographic variables include a combination of the local and non-local topographic elements (Li et al., 2018). Data on precipitation and temperature were obtained from the WorldClim archives (http://www.worldclim.org/). The spatial resolution of these datasets was resampled to 3m to match the spatial resolution of fused datasets (Rehman et al., 2023). All datasets were then imported into GEE platform for further analysis.

Table 5. 2. Indices generated, their description and formulae.

Spectral indices	Formula	Bands Used
NDVI	$\frac{NIR - Red}{NIR + Red}$	Arogoundade et al. (2023a)
NDVI1	$\frac{RedEdge1 - Red}{RedEdge1 + Red}$	Dalen et al. (2020)
NDVI2	$\frac{RedEdge2 - Red}{RedEdge2 + Red}$	Dalen et al. (2020)
NDVI3	$\frac{RedEdge3 - Red}{RedEdge3 + Red}$	Arogoundade et al. (2023a)
SR1	$\frac{NIR - Red\ Edge1}{NIR + Red\ Edge1}$	Ramoelo et al. (2015c)
SR2	$\frac{NIR - Red\ Edge2}{NIR + Red\ Edge2}$	Ramoelo et al. (2015c)
SR3	$\frac{NIR - Red\ Edge3}{NIR + Red\ Edge3}$	Ramoelo et al. (2015c)
SR	$\frac{NIR}{Red}$	Loozen et al. (2019)

Table 5.3. The topographic variables used in this study

Variable	Description
Elevation	Altitude above sea level
Slope	The steepness of the terrain
Aspect	A slope's compass direction
Wind effect	Wind speed and direction effects on the surface
Topographic wetness index	Calculates terrain water accumulation with respect to differences in elevation
Plan curvature	Curvature in a horizontal plane
Catchment area	Run off of water flow
Profile curvature	Curvature direction of the slope in the vertical plane
Positive openness	Convexity of surface
Negative openness	Concavity of surface
General curvature	Vertical and horizontal curvature
Standardized height	The relative height and slope positions
Convergence index	Computes ridges and valleys
Terrain roughness index	Calculates terrain heterogeneity
Sky view factor	Sky visibility
Distance from river	Areas near river
Slope length factor	The impact of slope length on erosion
Direct insolation	Solar radiation
Mass balance index	Terrain analysis
Valley depth	Valley's relative height

5.2.6 Statistical analysis

5.2.6.1 Random forest (RF) algorithm

Random forest (RF) algorithm, developed by Breiman (2001b), was used to estimate the C:N ratio due to its simplicity and robustness. RF is a non-parametric machine learning approach that integrates multiple decision trees to produce precise predictions (Ramoelo et al., 2015c). According to Adelabu et al. (2015), the strength of RF lies in its ability to build trees from training data points. Each tree is constructed from randomly selected subset of predictor variables (Ramoelo et al., 2015c). To improve model optimization, RF uses two parameters: *ntree*, which utilizes several subsets of decision trees, and *mtry*, which considers predictor variables at each tree node (Breiman, 2001b). RF can also distinguish predictor variables that are influential in estimating the C:N ratio based on the variables' important scores. The RF variable importance scores are calculated using the lowest Gini Index, a variable selection metric that measures the variable's accuracy in relation to the output model (Zhou et al., 2016). The *ntree, mtry,* and nodesize values were altered to improve the accuracy of the final models (Breiman, 2001b). To validate the prediction models, all datasets were randomly divided into 30% for testing and 70% for training (Peerbhay et al., 2016). To predict the C:N ratio within the rangeland, RF models were developed using (i) the fusion of Sentinel 2 and Planet scope spectral datasets, and ii) fused datasets integrated with topo-climatic variables. Finally, the best performing model was used to map the spatial distribution of the C:N ratio.

5.2.6.2 Accuracy assessment

To assess the accuracy of the regression models in predicting the C:N ratio, we used the coefficient of determination (R^2) and root mean square error (RMSE) (Pullanagari et al., 2012, Singh et al., 2018). R^2 measures the magnitude of variation that exist between the observed and predicted samples (Singh et al., 2018). Its values vary from 0 to 1, with values closer to 1 indicating a model's goodness of fit (Singh et al., 2018). The RMSE examined the prediction error between the predicted C:N ratio variables and observed field measurements (Singh et al., 2018). In addition to evaluating the predictions of RF quantitatively, the individual contributions of variables to each model were determined.

5.3 Results

The descriptive statistics of the measured forage C:N ratio, derived from field assessments conducted across 120 grassland plots are summarized as follows: minimum (14.42), maximum (40), mean (22.7), and standard deviation (5.21).

5.3.1 Performance of the C:N ratio estimation models

Figure 5.1 shows the C:N ratio estimates, and the performance of the predictive models based on both training and validation datasets. Although a strong correlation between predicted and observed values are noted for both models, the accuracy of the C:N ratio estimates from the fused dataset integrated with topo-climatic variables surpassed that of the standalone fused datasets. Specifically, the fused datasets yielded accuracies of R^2 from 0.78 to 0.83, and RMSE values from 2.16 to 2.39 for the calibration and validation models, respectively. Conversely, the integration of fused datasets with topo-climatic variables exhibited superior accuracies, with R^2 values of 0.89 to 0.86, and RMSE values of 2.06 to 2.10 for the calibration and validation models, respectively. These findings underscore the significance of incorporating multisource data for predicting and modelling foliar nutrients.

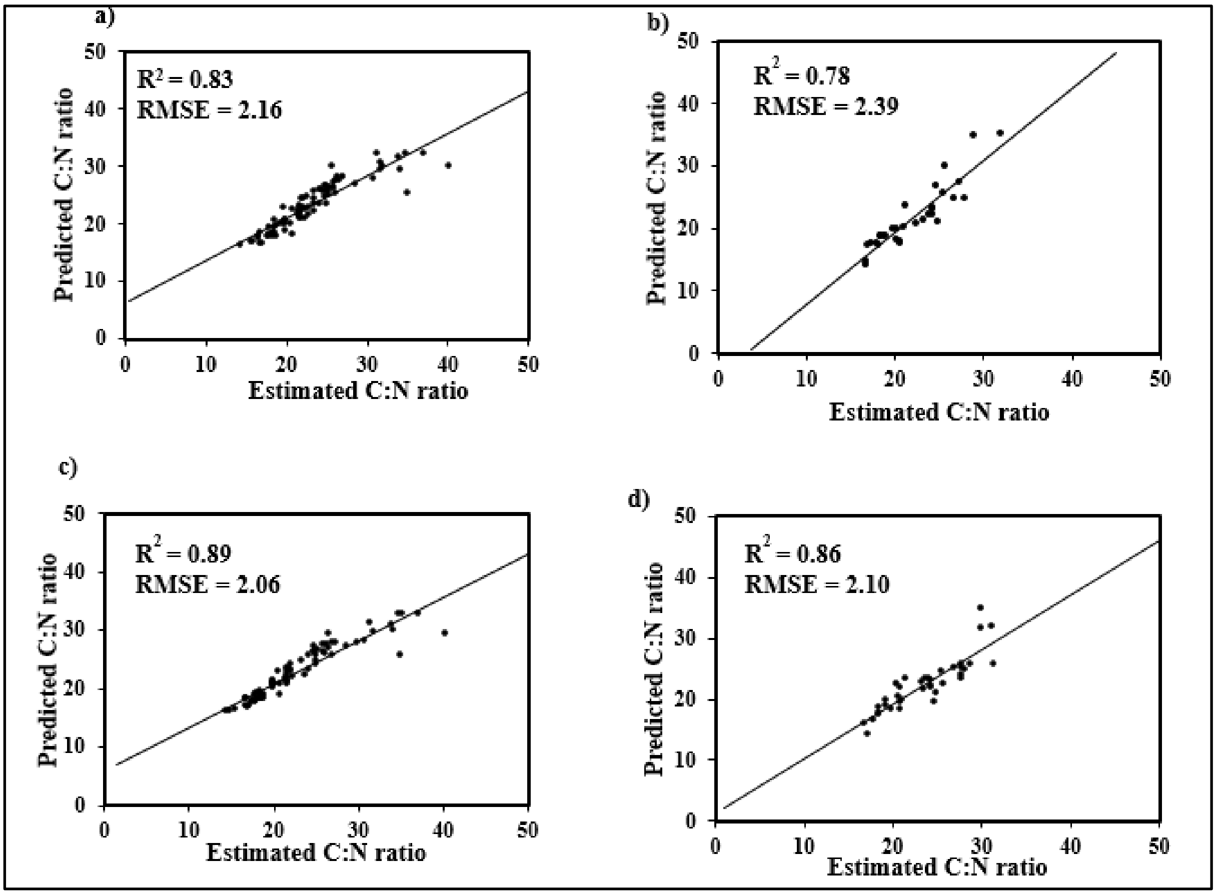

Figure 5.1. Observed versus predicted C:N ratio derived from the fusion of Planetscope and Sentinel 2 MSI for (a) calibration (b) validation as well as fused datasets integration with topo-climatic variables for the (c) calibration and (d) validation models.

Figure 5.2 illustrates the variable importance of the different models in predicting the C:N ratio. Based on Fig. 3a, bands 6, 8a, 7,8, and 3 (NIR, red edge, and green bands) as well as SRI emerged as the most important variables for predicting the C:N ratio. Meanwhile, in the model incorporating topo-climatic and fused datasets (Fig 3b), the most influential predictor variables for estimating the C:N ratio were bands 6,8a,7, 8 (red edge, NIR and green bands) as well as SR1, wind effect, SR2, and the topographic wetness index.

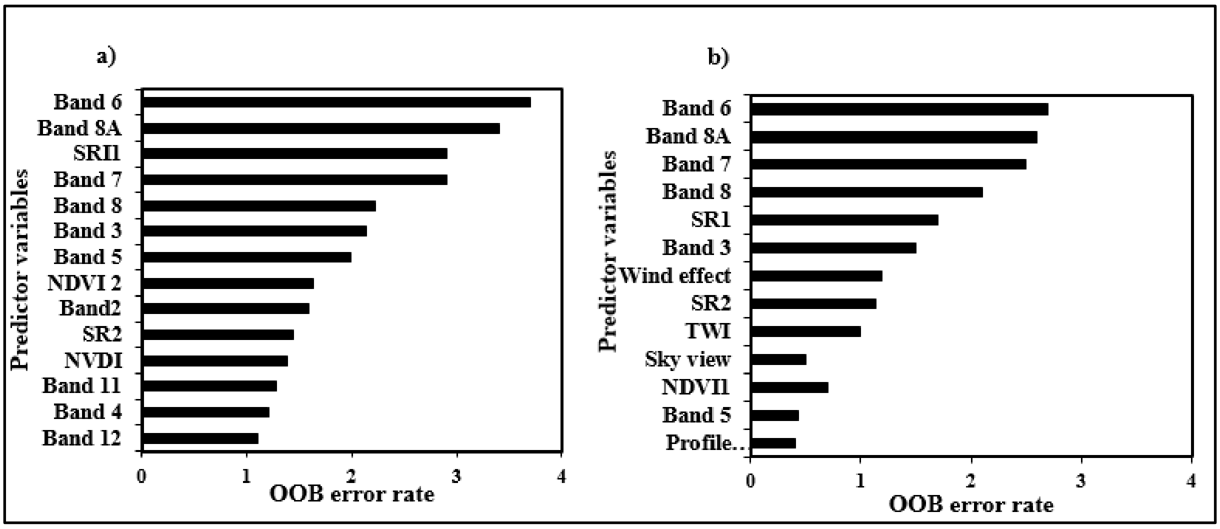

Figure 5.2. Variable importance in predicting C:N ratio using (a) fused data sets (b) integration of environmental variables and fused data. Increasing OOB error rates indicate higher variable importance.

5. 3.2 The C:N ratio spatial distribution

The modelled C:N ratio, derived from the random forest regression using fused datasets integrated with topo-climatic variables, ranges from 16 to 33 (Fig 5.3). The spatial representation of the foliar C:N ratio reveals higher C:N ratio in grass-dominated landscapes with low-quality pastures, whereas lower C:N ratio is in forage with good quality. Grasslands with good forage quality (lower C:N ratio) dominates the southern, central and the north-western parts of the rangeland, whereas the western part of the rangeland have poor forage quality (higher C:N ratio). This C:N ratio distribution map holds valuable insights for assessing forage health, and guiding land managers, and policymakers on optimal grazing management practices.

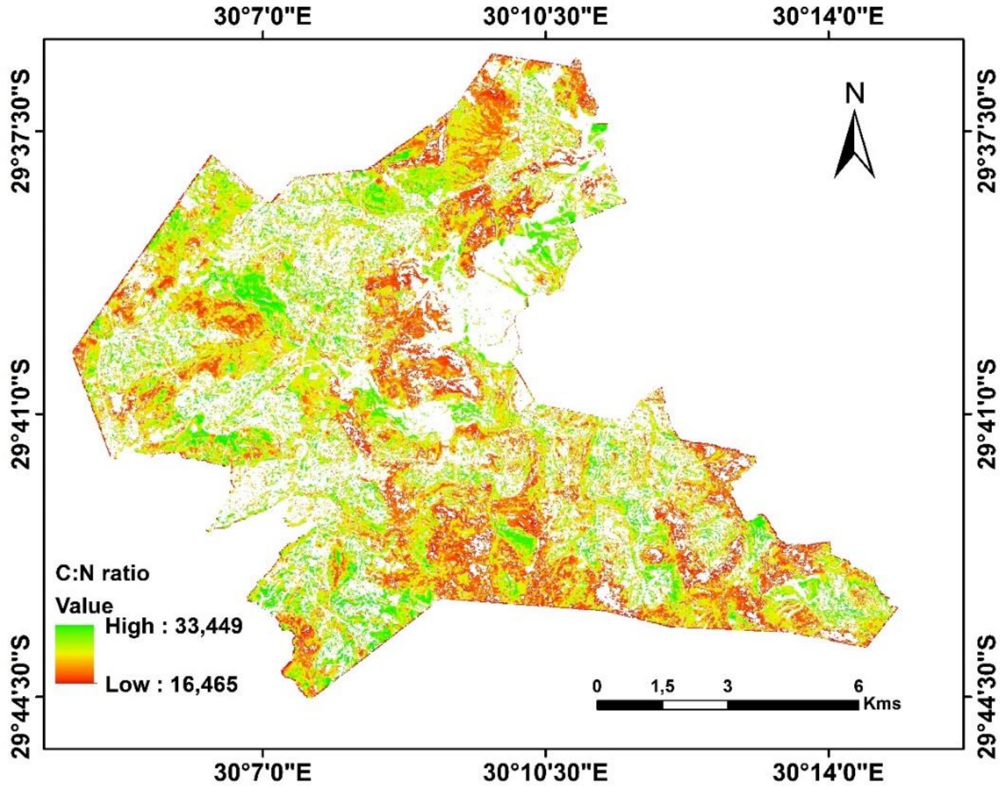

Figure 5.3: Spatial distribution of foliar C:N ratio in the study area.

5.4 Discussion

This study aimed to advance the methodology for mapping spatial variability in the C:N ratio as a key indicator of accessible forage quality, thereby contributing to proactive and efficient rangeland management strategies. Our study highlights the potential of leveraging multisource datasets through the application of the random forest algorithm to predict the C:N ratio within a diverse landscape in a communal area of South Africa.

The findings of this study show that the accuracy of the C:N ratio increased significantly for the model with fused datasets (Planetscope and Sentinel 2 MSI) integrated with environmental variables (RMSE= 2.16), against the fused datasets alone (RMSE= 2.39). Consequently, the fused dataset model corresponds to previous work by Arogoundade et al. (2023a) in the same region, who achieved an RMSE = 2.36. Nevertheless, by integrating fused datasets and topo-climatic variables, our approach achieved superior performance, reaching an accuracy of RMSE=2.14 in forecasting the C:N ratio in rangeland ecosystems. This performance can be attributed to the combination of the unique spectral attributes of Sentinel-2 imagery and Planet-Scope's impressive high spatial resolution, as well as the incorporation of crucial environmental variables. The spectral capabilities of Sentinel-2 exhibit heightened sensitivity to foliar nutrients like chlorophyll, nitrogen, and carbon-based constituents, whereas Planet-

Scope's spatial resolution (3.7m) provides detailed information important for distinguishing plant features, especially in heterogeneous grasslands (Arogoundade et al., 2023a). Furthermore, the inclusion of topographic variables proved instrumental in capturing the spatial variations of the landscape, which influences both plant nutritional resources and moisture availability. The value of integrating multisource datasets in mapping vegetation properties is consistent with previous literature (Marcinkowska-Ochtyra et al., 2019, Dube and Mutanga, 2016, Knox et al., 2012). For instance, Marcinkowska-Ochtyra et al. (2019) demonstrated improved accuracy in mapping specific habitats within a grassland ecosystem in Poland by fusing multi-temporal hyperspectral data with topographic indices. Similarly, Knox et al. (2012) reported enhanced accuracy in modelling forage quality in Kruger National Park, South Africa, through the integration of ecological variables with spectral data. This underscores the significance of considering a comprehensive set of pertinent variables for a more robust and accurate assessment of vegetation properties in rangeland environments.

In our investigation, the C:N ratio in rangeland exhibited sensitivity to specific spectral bands, including red edge, near infrared (NIR), and SR1, along with environmental factors like wind effects, sky view, and topographic wetness index. Notably, the red edge and NIR bands played pivotal roles in optimizing the accuracy of our predictive model for the C:N ratio. The alignment of our findings with earlier studies reinforces the robust performance of the red edge and NIR regions in forecasting the C:N ratio in plants (Arogoundade et al., 2023d, Xu et al., 2018, Durante et al., 2014, He et al., 2006a). This alignment is attributed to the inherent significance of the red edge and NIR regions within the electromagnetic spectrum, particularly in gauging foliar nutrients due to their heightened sensitivity to plant stress and health (Singh et al., 2018, Brewer et al., 2022). The reliability of estimating foliar nutrients using the red edge and NIR regions can further be attributed to their heightened sensitivity to nitrogen, chlorophyll, protein, and carbon-based constituents in plants, which form integral components for predicting the C:N ratio (Xu et al., 2018).

The relationship between the red edge, chlorophyll and nitrogen has been widely documented in literature (Cho and Skidmore, 2006, Chabalala et al., 2020a, Ali et al., 2022). Notably, the red edge band centred at 740nm (band 6) emerged as the most influential variable in predicting the C:N ratio. According to Cho and Skidmore (2006) and Ramoelo et al. (2015a), the 740nm region is highly sensitive to plant health as well as biophysical properties/structure (biomass). Additionally, the green band was also found to be sensitive to vegetation condition in this study. The green region of the electromagnetic spectrum is particularly sensitive to changes in plant pigments, especially during moderate to high increases in chlorophyll levels throughout plant growth (Schlemmer et al. (2013). These results align with the findings of Vasudeva et al. (2021), and Durante et al. (2014) who identified the green and NIR bands as important predictor variables in estimating nitrogen and carbon based constituents, which are related to the C:N ratio within the same rangeland.

Vegetation indices derived from the near-infrared (NIR), and red-edge bands, specifically the Simple Ratio Index (SR1), played a pivotal role in optimizing our model's estimation. The efficacy of this index can be attributed to their inclusion of the NIR band, renowned for its sensitivity to variations in leaf structure and its ability to detect changes in foliar nitrogen and carbon. In particular, the simple ratio index (SR) has demonstrated its efficacy in predicting foliar nutrient variability within South African rangelands, as previously demonstrated by Ramoelo and Cho (2018). Although, the red edge indices were also found to be amongst some of the important determinates of the C:N ratio, only the SR1 featured within the important variables in the fused datasets. This contradicts the findings of Arogoundade et al. (2023d), who reported that red edge based VI produced a higher accuracy when modelling the C:N ratio. This is likely because in the multi-source model, the topo-climatic variables were found to play a crucial role in the variability of C:N ratio in the rangeland. Specifically, the wind effect factor, topographic wetness index, and the Sky view factor were found to be the most important.

Wind, a component of climate, impacts various aspects of plant physiology, including leaf transpiration, airflow regulation, photosynthesis, disease spread, and ultimately, plant development and productivity (Burgess et al., 2016, Onoda and Anten, 2011, Aylor, 1990). In their study, Momberg et al. (2021) reported that wind condition (exposure and speed) was an important predictor variable that influences plant species richness, composition and nutrient variability beside other potentially eco physiologically important variables such as soil moisture, pH, solar radiation and depth. For instance, at higher altitudes, where the speed of wind is faster, plants close their stomata to limit transpiration, thereby lowering the rate of photosynthesis (Grossiord et al., 2020, Sun et al., 2020a). As a result, wind effect tends to facilitate the rangeland's foliar nutritional variability, including the C:N ratio, at lower or intermediate altitudes. Additionally, the topographic wetness index (TWI), a crucial indicator of the distribution of water in the soil, has an impact on the C:N ratio (Kopecký et al., 2021). TWI reflects the movement of water across the terrain, impacting the soil's capacity to retain moisture, thus influencing the spatial variability of foliar biochemical composition and plant production (Kopecký and Čížková, 2010). For instance, low-lying areas, characterized by greater soil moisture content, nutrients, and depth, promote plant growth compared to higher areas, which typically face harsh weather conditions and limited vegetation growth due to soil micro-organism deficiencies (Semeraro et al., 2022). In related studies, Moeslund et al. (2013), and Sibanda et al. (2021) reported that topographically controlled soil moisture promotes plant diversity patterns and foliar nutrient variability.

Additionally, our study highlights the impact of the sky view factor as a surrogate for relief illumination, which represents the amount of radiation reaching the earth at a given angle (Dubayah and Rich, 1995). The sky view factor, like aspect, delineates the quantity of radiation available for plants without obstruction, crucial for photosynthesis and respiration (Gumede et al., 2022). According Guo et al. (2021) and Gumede et al. (2022), increased radiation/optimal exposure to sunlight in plants facilitates photosynthesis and improves microbial activity, thus affecting the net primary production (NPP) which are related with biomass production. Therefore, regions with a high sky view factor are more productive (have a lower C:N ratio), whereas regions with little radiation exposure often have lower rates of photosynthetic activity. Accordingly, in this study, locations with high visibility will often support better grass productivity (lower C:N ratio), while areas with lesser visibility likely have lower rates of photosynthesis, leading to higher C:N ratios. Therefore, variations in the accessibility of radiation contributed to the fluctuation of foliar nutrients, such as the C:N ratio.

The C:N ratio spatial variability map in the rangeland shows that the C:N ratio is higher in grassland with poor forage quality compared to grasslands with good forage quality. Specifically, the southern region of the study site has a lower C:N ratio, pointing to ideal forage for livestock. Conversely, the western and central areas exhibit higher C:N ratios, signalling sub-optimal forage quality and quantity. Examining the study site reveals that the western areas, near human settlements, experience heightened grazing activities, which likely contributed to increased livestock grazing — resulting in low biomass and diminished forage quality. This is supported by Jamil et al. (2022) and Anderson and Hoffman (2007), who reported that rangelands near human settlements are prone to severe encroachment and degradation, characterized by reduced species diversity, less palatable grass species, and poor regeneration. These factors likely contribute to the observed poor forage quality (high C:N ratio) in the western and central regions, particularly given the prevalent practice of free-ranging in communal areas. Furthermore, various factors influencing foliar nutrients in plants, such as species composition, environmental conditions, local habitat, and rangeland management practices, may contribute to spatial differences in the C:N ratio experienced across the rangeland (Kerkhoff et al., 2006, Knox et al., 2012). For instance, Phillips et al. (2006) demonstrated a higher C:N (>30) ratio in rangelands affected by drought in the mixed-grass environment. Also, Kunz et al. (1995) modelled the spatial variability of the C:N ratio in Southern Africa under future climate scenarios. In regions where the C:N ratio was predicted to decrease, it was assumed that assimilation of nitrogen would grow, relative to carbon in the future climatic scenario. Similarly, regions with higher C:N ratios suggest that assimilated carbon would increase compared to nitrogen. Hence, climatic variability due to enhanced greenhouse effect (Soares et al., 2019), and human induced environmental changes (burning, and use of fertilizers) which influence plant nutrition, may have contributed to the C:N ratio spatial variability in the rangeland. Furthermore, the study conducted by Beeri et al. (2007) and Durante et al. (2014) demonstrated that management strategies for rangelands (such as grazing, burning, and fertilization) and the type of grass can influence the variance in C:N spatial distribution due to their effects on the biochemical characteristics of the grass.

This study has demonstrated an alternative framework for assessing rangeland health using fused datasets (Sentinel 2 and Planet scope) as well as the integration of environmental variables. The results show that the integrating fused datasets with topo-climatic variables improve the estimation of the C:N ratio compared to standalone datasets. This information is important to rangeland stakeholders and decision makers on fostering sustainable utilization of rangeland resource for optimal grazing management. In addition, future studies can benefit from upscaling the monitoring of foliar C:N ratio in rangelands to a regional level using recent and freely available satellite with greater spatial resolutions such as Sentinel 3 multispectral sensor. Other factors that affect the distribution of plant nutrients can also be considered, such as moisture content and soil analysis. Lastly, it is critical to investigate how future climate change can impact the foliar C:N ratio, which in turn influences wildlife migration and grazing patterns.

5.5 Conclusion

This study concludes that,

- Combining the benefits of fused datasets with environmental variables (R^2 = 0.82, RMSE = 2.14) improves the prediction accuracy of foliar C:N ratio compared to fused datasets (R= 0.78, RMSE = 2.39) alone.

- The C:N ratio can be optimally estimated using spectral derivatives from the red edge, NIR, green bands, red edge derived simple ratio, as well as environmental variables such as wind effect, topographic wetness index, and sky view.
- The prediction of foliar C:N ratio as an indicator for rangeland quality and quantity in this research provides a robust, efficient and timely monitoring of rangeland health conditions, necessary for sustainable rangeland management and economic development.

Chapter Six: Remote sensing of rangeland quality at a landscape scale: A synthesis

6.1 Introduction

Rangelands are prized for their livestock and wildlife feed and ecological significance, especially in communal areas (Mlaza et al., 2023, Ravhuhali et al., 2022). The rural economy and livelihoods rely on rangelands for grazing, fuelwood for heating and agricultural production (crop and livestock production) (Ulziibaatar and Matsui, 2021). However, the increasing pressure on theses natural resources, due to, among others, invasive species, urbanization and climatic change remains a challenge in communal areas, particularly in developing nations (Abdulahi et al., 2016, Al-Bukhari et al., 2018). Rangeland degradation results in a decline in grass productivity and quality, thereby affecting animal grazing and food security (Sainnemekh et al., 2022). Rangeland quality can be evaluated based on its nutritional value (Royimani et al., 2021, Petit Bon et al., 2022). Foliar carbon (C) and nitrogen (N) are important in plant development, and their ratio is widely used in ecological and climate change research (He et al., 2006a, Zhang et al., 2020, Xu et al., 2018). The C:N ratio is a measure of the limitation and utilization of C and N, which influences the growth, species composition, leaf respiration, and health in plants (Xu et al., 2018). The C:N ratio is an important criterion in classifying grassland nutrition, which is useful for understanding the composition of nutrients and forage quality in rangeland during the stages of development (Gao et al., 2020a, Berri, 2007). The spatial variability of the C:N ratio in rangelands influences forage resources productivity, and consequently livestock grazing and distribution (Arogoundade et al., 2023a). Therefore, information on the spatial distribution of the C:N ratio is required to aid rangeland managers in sustainable rangeland management. In this regard, this study sought to establish affordable and efficient datasets and techniques in predicting the C:N ratio within a communal rangeland. This is important in understanding livestock grazing patterns and movement, as well as identifying hot spots for conservation and restoration.

Historically, foliar nutrient assessments have traditionally relied on field surveys and laboratory analysis, but these methods are limited due to their exorbitant prices, intensive labour and only applicable to small areas (Stergiadis et al., 2015). By contrast, earth observation technology provides the opportunity to detect foliar nutrients such as the C:N ratio in near real-time, repeatedly and at varying spatial extents across different landscapes (Xu et al., 2023, Wang et al., 2022). Taking the above into account, there is the need to consider cost – efficient modem day multispectral sensors such as Sentinel 2 MSI and Planetscope with improved spatial, spectral, radiometric, and temporal resolutions in establishing effective datasets to predict and map forage C:N ratio across local and regional extents. Also, the monitoring of forage nutrients such as the C:N ratio requires efficient algorithms and data processing packages that are quick with powerful statistical analysis of datasets at varying spatial scales. The Google Earth Engine (GEE) cloud computing platform with built in machine learning algorithms such as the random forest can integrate and analyse several input variables, while overcoming multi-collinearity problems in monitoring foliar C:N ratio (Srinet et al., 2020). To facilitate strategic grazing plans and effective rangeland management, herders could benefit from understanding the environmental drivers in the spatial variability of grass quality in rangelands. This would enhance their understanding of livestock and wildlife grazing patterns and distribution. Therefore, this study explored the application of remote sensing in predicting the spatial distribution of the C:N ratio as proxy for rangeland quality, which can be used to develop effective techniques for continuous monitoring and mapping of rangelands resources, particularly in resource constrained countries.

6.2 Conclusion

This study sought to explore the utility of modern-day multispectral sensors with ancillary variables in predicting and mapping the spatial distribution of foliar C:N ratio within a heterogeneous landscape at a fine scale in southern Africa. The findings of this study demonstrated the value of topo-climatic variables, modern day multispectral sensors such as Sentinel 2 and Planet scope, image processing techniques (data fusion) combined with non-linear algorithms such as the random forest in mapping the foliar C:N ratio at a landscape scale. Therefore, this study concludes:

1) Progress on the use of foliar nutrients such as carbon and nitrogen in mapping rangeland quality is well documented, however, there is a gap in mapping foliar C:N ratio in rangelands, especially in Africa. Evidence from literature reveals that most studies have focused on mapping foliar C:N ratio of plants using hyperspectral data. In addition, while exorbitant prices and unavailability of high-resolution sensors were identified as limitations in mapping forage C:N ratio at a fine scale, the use of advanced freely available Sentinel 2 MSI in mapping the C:N ratio in rangelands remains to be explored. Finally, the predictive

accuracy of foliar C:N ratio depends on sophisticated machine algorithms that are flexible and can reduce multi-collinearity amongst predictor variables.

2) Leveraging the Google Earth Engine (GEE) cloud computing platform, open source medium spatial resolution Sentinel 2 MSI with the random forest (RF) algorithm successfully predicted the C:N ratio in the rangeland with reasonable accuracy. The results in this study demonstrate that the spectral properties of Sentinel 2 MSI (13 spectral bands between 490 to 2190 nm), 5 days’ re-visit and 290km swath width is an invaluable source of primary dataset in the continuous and long-term monitoring of rangeland health, especially in data scare areas. The red edge, NIR bands as well as the IRECI and EVI indices were influential variables in estimating the C:N ratio in the rangeland. The study demonstrated the effectiveness of inbuilt RF model within the GEE in retrieving spectral information for rangeland monitoring.
3) That the prediction accuracy of foliar C:N ratio in the rangeland was enhanced by fusing the Sentinel 2 and Planetscope datasets using the pixel fusion approach and the random forest algorithm as opposed to individual sensors. The high spatial resolution of Planetscope complemented the spectral settings of Sentinel 2 to improve the predictive accuracy of foliar C:N ratio in rangeland. Furthermore, as individual sensors, the high spectral resolution of Sentinel 2 was more valuable compared to the high spatial resolution of Planetscope in estimating foliar C:N ratio in the heterogeneous landscape. The red edge, near infrared and visible region of the electromagnetic spectrum contributed significantly to the model’s prediction.
4) Fused datasets with improved spatial and spectral settings can improve the accuracy of foliar C:N ratio compared to individual sensors. This chapter provides substantial evidence that multisource data (fused datasets integrated with ancillary variables) provide better estimates of foliar C:N ratio compared to fused datasets as stand-alone variables using the random forest algorithm. The key predictor variables which significantly influenced the spatial distribution of the C:N ratio are red edge (748 and 793 nm) and near infrared (900 nm) bands, wind effect, topographic wetness index, and the sky view factor. This study demonstrates the utility of multi-source remotely sensed data in providing invaluable data set for monitoring forage nutrients at a landscape scale.

6.3 Recommendation for future research

This study provides insight on the possibility of obtaining accurate near real-time spatially precise information about rangelands health/ nutrient levels, as well as the interacting influence of significant environmental variables, using advanced satellite sensors and the RF algorithm. This is particularly important in developing countries where there is data constraint, and hyperspectral sensors are expensive and not readily available. Information on rangeland health is key for effective management of rangeland resources and designing of appropriate grazing plans. In addition, monitoring the C:N ratio as an indicator of rangeland health can contribute towards achieving the United Nations' Sustainable Development Goals 1, 2, 12, and 15 which advocates for the provision of policy solutions and technology that addresses hunger, food security, biodiversity and mitigation of climate change (Agarwal, 2018, Carlsen and Bruggemann, 2022). As a result, the research's findings, and frameworks will greatly advance Southern Africa's current understanding of rangeland management and conservation, while enhancing earth observation for the prosperity of Africa. Based on the findings of this study, the following recommendation and prospects should be considered for future research.

1) While the red edge position of Sentinel 2 MSI in this study showed promising results, there is the need for future investigation to focus on the application of the near infrared regions of modern generation multispectral sensors in mapping the C:N ratio due to their significance in this study.
2) The spatial variability of forage nutrients is often influenced by phenology, plant development and senescence. Therefore, future studies should focus on the detection of the C:N ratio across different growth stages using freely available high temporal resolution data such as the Sentinel series. Also, it is vital to investigate how forage nutritional quality (C:N ratio) responds to climate change, as this impacts grass quality and quantity and, consequently, livestock grazing and dispersal.
3) Although the use of radiative transfer models (RTMs) such as the PROSPECT-PRO have proven to be useful for biochemical properties in plants, their use in estimating C:N ratio in heterogeneous environments needs to be further explored.
4) Although Sentinel 2 performed well in this study, future studies should explore and compare the utility of freely available medium spatial resolution sensors, such as Landsat 9 with improved signal-to-noise ratio in estimating the C:N ratio, especially in rangelands at a regional scale.

5) Future studies could benefit from including other factors that influence the spatial variability of forage nutrients such as soil characteristics, geology and moisture content.

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