Evaluating the use of Sentinel-2 red-edge spectral information in estimating foliar C:N ratio within a communal rangeland ecosystem

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Abstract: *Foliar C:N ratio determines the quality and efficiency of nutrient distribution in rangelands. Thus accurate information on forage quality is important for optimal management of rangeland resources. Achieving this goal requires robust and cost-effective techniques that can be used to reliably monitor rangeland foliar nutrients. Remote sensing offers cutting-edge spectral information valuable for monitoring rangeland quality and productivity. Specifically, the application of red-edge region has been noted to be critically sensitive to changes in foliar nutrients concentration. Using the random forest regression, this study aims to examine the strength of Sentinel-2's red-edge spectral information in mapping foliar C:N ratio. Sentinel 2 image data and one hundred and twenty grass samples were used to predict the foliar C:N ratio. The results showed that red-edge spectral data produced higher accuracy (R^2 = 0.78 and RMSE of 2.34) than traditional spectral data without red-edge inclusion (R^2 = 0.69 and RMSE of 2.40). However, optimal accuracy was achieved when the traditional and red-edge spectral data were integrated to an R^2 of 0.83 and RMSE of 2.14. This study demonstrates the value remote sensing in mapping forage quality.*

Keywords: C:N ratio, Sentinel 2, Rangelands, Red edge region, Random Forest

Introduction

Wildlife and livestock distribution and health significantly depends on rangeland quality and productivity (Kahumba & Tefera, 2023). Furthermore, rangelands provide habitat for a wide range of biodiversity and valuable ecosystem services that include carbon sinks, soil nutrient retention and water purification (Angerer et al., 2023; Jamil et al., 2023). Thus, knowledge on grass quality is necessary for effective rangeland management and grazing plans to ensure sustainable rangelands and animal productivity. Commonly, rangeland productivity and health can be determined by their forage nutrients, which are primary indicators of vegetation ecosystem quality (Ishaq et al., 2019), and yield (Xu & Guo, 2015). Literature has demonstrated that nitrogen (N), and carbon (C) are key nutrients for vegetation productivity and quality (Adjorlolo et al., 2014; Naicker et al., 2023). Such nutrients, also play a critical role in plant physiological response, particularly the absorption of active photo synthetically radiation and nutrient cycling (Duan et al., 2023; Osorio et al., 2014). Despite numerous studies exploring foliar C and N to understand rangelands quality (Dehghan-Shoar et al., 2023; Wang et al., 2022), there is paucity in studies assessing ecological stoichiometry ratios, especially the C:N ratio. This ratio is critical for determining the minimum nutrient threshold required by grazing animals in rangelands (Arogoundade et al., 2023; Berri, 2007). Furthermore, C:N ratio critically indicates the balance between C and N levels used by plants for their growth and reproductive capacity (Gao et al., 2020). According to Phillips et al. (2006) and Asner et al. (1997), C:N ratio is an essential indicant of the amount of litter decomposition, mineralization and soil organic matter. It has been suggested, high-quality forages have a C:N ratio between 24 to 30, whereas low-quality forages (low C:N ratio - less nitrogen than carbon) typically has an increase in C:N ratios above 30 (Arogoundade et al., 2023; Beeri et al., 2007). In this regard, the foliar C:N ratio plays an important role in determining rangeland nutritive quality. Hence, it is necessary to continuously map foliar C:N ratio to understand and monitor rangelands growth and grazing regimes. This information is valuable for tracking potential nutrient deficiencies in rangeland, which could compromise rangeland ecosystem health and quality. To achieve this goal, cost-efficient, precise, and robust methods and datasets must be developed to map the foliar C:N ratio within rangeland ecosystems.

Remote sensing offers spatially explicit information essential for mapping foliar nutrient dynamics in rangelands (Askari et al., 2019; Sharifi, 2020). Compared to laboratory techniques, remote sensing technology has proven to be a cost-efficient, fast and a reliable source of primary data for mapping and monitoring of rangeland health and quality. Specifically, the advent of freely available medium-to-fine spatial resolution Sentinel 2 multispectral image (MSI) with cutting-edge signal sensing properties offers better opportunity for precise mapping and monitoring of foliar C:N ratio within rangeland (Guevara-Torres et al., 2024). Sentinel 2's popularity in modelling and monitoring vegetation health and quality is attributed to its improved spatial, spectral and radiometric properties (Abdullah et al., 2019; Chabalala et al., 2020b). The sensor is characterised by varying spatial resolutions between 10 to 60 m, and uses 13 spectral wavebands to acquire spectral information with 5-day revisit, critical for frequent mapping of forage C:N ratio (İleri & Koç, 2022; Madonsela et al., 2023). Sentinel 2 has strategically positioned bands covering the unique red-edge region of the electromagnetic spectrum that is critically sensitive to vegetation spectral reflectance

Amongst the spectrum regions, the strategically positioned red-edge region has been determined as critical for detecting and recording rapid change in plants chlorophyll concentration, hence sensitive to vegetation spectral response (Cho et al., 2012; Curran, 1989). In this regard, the red-edge region can be effectively used to determine plant conditions related to nutrients deficiency, drought stress and biomass quality and quantity (Herrmann et al., 2010). Numerous studies have explored the red-edge's application in mapping or estimating plant nutrients including chlorophyll, nitrogen, cellulose and lignin (Ge et al., 2011; Ramoelo et al., 2011; Sellami et al., 2022). However, such research relied on hyperspectral imaging analysis, which has a number of disadvantages, including high cost and unavailability (Lu et al., 2020; Teke et al., 2013). These limitations may hinder continuous monitoring of rangeland’s foliar C:N ratio, particularly in resource- poor countries. Thus, this study sought to examine Sentinel-2 red-edge wavebands and spectral indices in mapping foliar C:N ratio within a communal rangeland using the random forest algorithm.

Methodology

This study was conducted in the Vulindlela communal rangeland in KwaZulu-Natal province of South Africa (Fig 1). The field data collection and survey were carried out on the 28th of March to the 1st of April 2022, during summer season when weather conditions are favourable for maximum biomass productivity. Approximately 120 pre-determined sampling points were established based on purposive sampling strategy. In each sampling plot, two 1m × 1m subplots were randomly established to capture plot variability, then, grass samples were clipped and sent to laboratory for C:N ratio extraction using an elemental analyser.

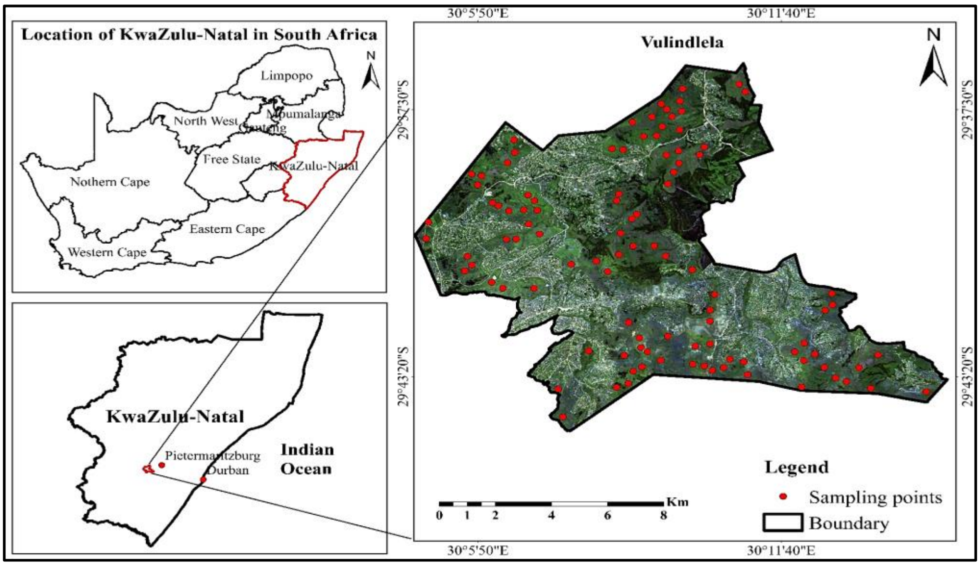

Figure 1. The location of Vulindlela communal area in KwaZulu-Natal, South Africa.

In addition, Sentinel 2 MSI downloaded from the Google Earth Engine (GEE) was used to develop spectral data to estimate the C:N ratio. Using the code editor's filter tool in GEE, the image was filtered to the study area's boundary, from March 28th to April 1st, with 5% cloud cover. Sentinel 2 MSI is characterised by 13 bands – coastal aerosol (band 1), blue (band 2), green (band 3), red (band 4), red edge 1-3(bands 5,6 and 7), near infrared 1-2(bands 8 and 8A), water vapour (band 10) and short wave infrared 1-2 (bands 12 and13). Its spatial resolutions ranges from 10m to 60 m (Cisneros et al., 2020; Yu et al., 2024). This study eliminated bands 1, 9, and 10 from its analysis since they are unsuitable for analysing vegetation. Prior to running the prediction models, the dataset was randomly split into 30% for testing (36) and 70% for training (84) using the random forest regression (Kutlug Sahin & Colkesen, 2021). To determine the value of Sentinel 2 MSI in predicting the forage C:N ratio, we computed different vegetation indices (VI). We calculated several alternative Normalized vegetation indices (NDVIs) and Simple Ratios (SRs) using red edge bands (I, 2, and 3), in addition to the traditional NDVI and SR. These spectral indices were assessed based on their performance in prior research examining foliar nitrogen, carbon-based components, and chlorophyll in plants (Li et al., 2024).

The Random forest (RF) machine learning technique was employed for the C:N ratio estimation due to its robust nature (Breiman, 2001). RF was constructed by combining numerous decision trees and various bootstrap samples from the predictor variables. Using the bootstrap approach, the mean variable importance of each decision was estimated. Bootstrapping is the random resampling of samples from a set of observer data (Lopatin et al., 2016; Ramoelo et al., 2015) to improve the robustness of predictions in a model (Lee et al., 2020). For this analysis, every bootstrap iteration produced 84 plots with replacement using the 84 available samples. The remaining 36 samples were not used in the model analysis, but as independent validation data. The random forest regression models were then embedded with a bootstrap of 500 iterations to predict the C:N ratio from the validation dataset (36 observation). Then, the final predictions were calculated by averaging each tree's predictions. For each of the RF model, the mean root mean square error (RMSE), and mean coefficient of determination (R^2) from the 500 bootstraps were calculated and their accuracies used to evaluate the models. To estimate the C:N ratio, the RF was constructed, based on (i) Red-edge spectral data (ii) Traditional spectra data (without red-edge) (iii) Integrated spectral data. The optimal RF model (lowest RMSE and highest R^2) was employed to generate a map of the mean C:N ratio based on the 500 bootstraps.

$$R^2 = 1 - \sum \frac{(y_{measured} - \bar{y}_{predicted})^2}{(y_{measured} - \bar{y}_{predicted})^2} \qquad \text{Equation 1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_{measured} - \bar{y}_{predicted})^2}{n}} \qquad \text{Equation 2}$$

where $y_{measured}$ is the field observed C:N ratio , $\bar{y}_{predicted}$ is the projected C:N ratio, n is the total number of samples, and i is the predictor variables used in the analysis (Masenyama et al., 2023; Shoko et al., 2018).

Results and Discussion

The results in Table 1 show the predictive models for foliar C:N ratio estimation. The red-edge spectral data model produced better coefficient of determination (R^2: 0.78) and (RMSE: 2.34), compared to the traditional spectral data model without red-edge inclusion (R^2: 0.69, RMSE: 2.40). However, the integration of red-edge and traditional spectral datasets produced highest prediction performance (R^2: 0.83 and RMSE: 2.14) for foliar C:N ratio in the rangeland.

Table 1: Prediction models of Sentinel-2 spectral information

Model	Variable combination	R^2	RMSE
1	Red-edge spectral data	0.78	2.34
2	Traditional spectra data (without red-edge)	0.69	2.40
3	Integrated spectral data	0.83	2.14

The spatial distribution map (Figure 2) shows a snapshot distribution of the C:N ratio, and thus provides insight into the relationship between foliar C:N ratios and forage quality. The result shows that the forage C:N ratio ranges from 16.16 and 33.09. According to Phillips et al. (2006), C:N ratio <30 indicate high-quality forage, ideal for animal dietary requirement. Higher C:N ratios in the western part of the rangeland indicate poorer forage quality, indicating regions that require conservation or restoration to improve forage quality. However, some parts of the rangeland's south-western and central areas have good quality forage (lower C:N ratio), which may be suitable for livestock grazing.

Results show that red edge spectral data is critical in improving the prediction of foliar C:N ratio within the communal rangeland, compared to traditional spectral data (without red-edge). This can be attributed to the sensitivity of red-edge to numerous vegetation properties such chlorophyll, leaf area index, nitrogen and carbon-based constituents, valuable for measuring foliar C:N ratio (Ali & Imran, 2020; Misra et al., 2020). The red edge region is defined by a vertical change in vegetation spectra, particularly between 680 and 750 nm wavelengths, which strongly detect and record maximum vegetation chlorophyll concentration (Sellami et al., 2022). In this regards, our findings agree with the hypothesis suggesting that satellite sensors with unique strategically positioned bands within the red-edge region offer invaluable spectral information that can concisely measure crucial vegetation metrics such as foliar C:N ratio. The results also show that vegetation indices derived from the red edge-red edge simple ratio (Red edge SR) and Normalized difference vegetation red-edge index (NDVI red edge) are critically important in optimising the predictive performance of foliar C:N ratio. The strength of NDVI red edge in improving estimation performance of foliar C:N ratio can be attributed to the fact that the index provides spectral reflectance with reduced atmospheric, soil background and water absorption effects (Mngadi et al. 2022, Sun et al. 2019). Literature suggests that red-edge spectral indices can be precisely and explicitly utilized for determining vegetation health and quality such as C:N ratio (Chabalala et al., 2020a; Ramoelo et al., 2015). Furthermore, the robustness of spectral reflectance contained in red-edge derived indices is attributed to the fact that red-edge spectral wavebands detect and record rapid change in vegetation chlorophyll content and leaf pigments, valuable for mapping and monitoring spatio-temporal variations in vegetation health and quality, especially in rangelands (Mashiane et al., 2023; Munyati et al., 2020).

In addition, the results on the distribution map show that foliar C:N ratio varies in the study area. This variability can be attributed to topographic characteristics and uncontrolled grazing density within the area (Royimani et al., 2022). Literature has demonstrated that aspect, elevation and slope can significantly influence spatial variation in forage productivity and health across landscapes (Knox et al., 2012; Ramoelo et al., 2013). Also, patches of different species of grass existing in the area (i.e., *Alloteropsis semialata, Themeda triandra,* and *Eragrostis tenuifolia*) could have contributed to the variability of foliar nutrients due to the differences in the biophysical and biochemical properties (Wang et al. 2021, Chen et al. 2016, Niu et al. 2008). Niu et al. (2008) for instance, affirmed that changes in terrain and trait properties amongst grass species significantly influence variations in nutrients quality across rangeland landscape.

In addition to Sentinel 2 optimal red-edge indices, the use of robust random forest machine learning regression model improved the estimation accuracy of foliar C:N ratio. The strength of random forest algorithm lies in its ability to select important variables necessary for the best regression model (Bhattarai et al., 2023; Ramoelo et al., 2015). In this study for instance, the integration of SR_{RE} and $NDVI_{RE}$ selected by random forest regression model created an invaluable methodology for estimating and mapping foliar C:N ratio in rangelands. This study provides necessary information to rangeland management stakeholders on the adoption of freely-available and cost-effective Sentinel-2 MSI in understanding and monitoring of rangeland health and quality.

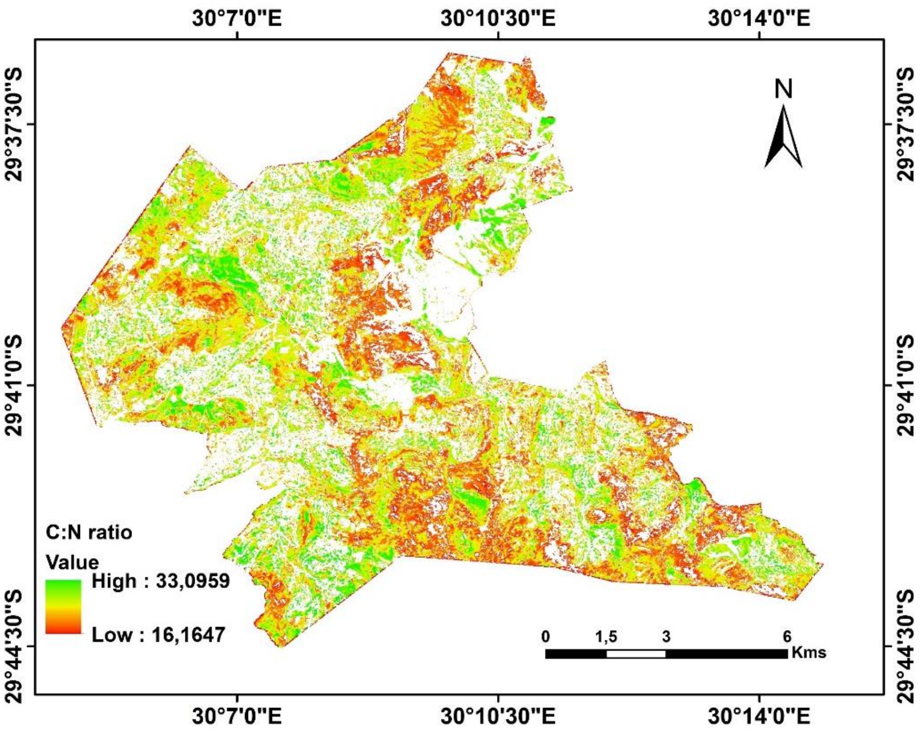

Figure 2: The spatial distribution of foliar C:N ratio produced using the integrated spectral dataset.

Conclusion

The results of this study are crucial for understanding rangeland grass health and quality. The study provides necessary information to rangeland management stakeholders and policy-makers to plan for optimal policies that govern rangeland health and quality. Overall, we deduce that Sentinel-2 red-edge spectral information can be precisely and concisely utilized in estimating and monitoring of grass foliar nutrients within rangelands. Also, the ensemble random forest regression model was robust and effective in optimally estimating rangeland grass foliar nutrients.

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