INTERNATIONAL JOURNAL OF REMOTE SENSING
2024, VOL. 45, NO. 14, 4737–4763
https://doi.org/10.1080/01431161.2024.2368929

Seasonal monitoring of biochemical variables in natural rangelands using Sentinel-1 and Sentinel-2 data

Monde Rapiya[a], Abel Ramoelo[b] and Wayne Truter[a]

[a]Department of Plant and Soil Sciences, University of Pretoria, Pretoria, South Africa; [b]Centre for Environmental Studies, Department of Geography, Geoinformatics and Meteorology, University of Pretoria, Pretoria, South Africa

ABSTRACT
Rangelands are natural ecosystems that serve as essential sources of forage for domesticated livestock and wildlife. Therefore, accurately mapping nutrient levels in rangelands is crucial for sustainable development and effective management of grazing animals. Remote sensing tools offer a reliable means to explore nutrient concentrations across large spatial areas. This study aimed to estimate and map seasonal foliar concentrations of nitrogen (N), phosphorus, and neutral detergent fibre (NDF) in mesic tropical rangelands of Limpopo using Sentinel-1, Sentinel-2, and the integration of S1 and S2 data. Fieldwork was conducted to collect samples for seasonal foliar nutrients (N, P, and NDF) during early-summer (November-January 2020), winter (July-August 2021), and late-summer (February-March 2022). Various conventional and red-edge-based vegetation indices were computed. The results demonstrate that integration data from S1 and S2 can effectively estimate and predict foliar concentrations of N, P, and NDF in mesic rangelands throughout the seasons, achieving R^2 values of 0.76, 0.78, and 0.71, with corresponding RMSE values of 0.13, 0.04, and 2.52. Notably, red-edge variables emerged as the most significant parameters for predicting seasonal N, P, and NDF concentrations. Additionally, factors such as season and slope significantly influenced the distribution and occurrence of these foliage nutrients, with higher foliage production observed during late-summer and on steeper slopes. The study concludes that the integration of S1 and S2 data can effectively monitor the seasonal dynamics of biochemical parameters. This finding holds significant implications for policymakers and rangeland users, offering a comprehensive understanding of the intricate variations within rangeland ecosystems. Further research could expand on these findings by applying the knowledge to various datasets, exploring different rangelands, and examining additional ecological factors such as slope altitude to detect foliar fibre biochemicals. Finally, the applications of this research extend beyond

ARTICLE HISTORY
Received 8 April 2023
Accepted 8 June 2024

KEYWORDS
Biochemical parameters; forage quality; rangeland; remote sensing; season

CONTACT Monde Rapiya u16400829@tuks.co.za Department of Plant and Soil Sciences, University of Pretoria, Private Bag x 20, Pretoria, Hatfield 0028, South Africa

individual properties, providing practical tools for sustainable rangeland management and informed decision-making in resource utilization and conservation.

1. Introduction

Rangelands are naturally occurring ecosystems primarily used as the forage source for domesticated livestock and wildlife (Alkemade et al. 2013; Spangler et al. 2012). Globally, rangelands account for over half of global ecosystems and play an important role in social well-being (Engler et al. 2018). However, despite the threats from climate change (Godde et al. 2020), the continuous increase in the global population has significant implications for rangeland utilization and management (Ramoelo et al. 2018). This population increase puts pressure on natural rangeland resources (goods and services) and often results in significant variations in seasonal forage production (Knox et al. 2011; Thornton 2010). Overusing natural rangelands can decrease grass quality and productivity, resulting in poor palatability and declining animal production numbers and market demand (FAO 2010; Ramoelo et al. 2018). The palatability of grass is known to directly impact livestock forage intake, affecting livestock production levels and food security (Knox et al. 2011). Therefore, the sustainable management of rangelands contributes to carbon absorption and storage to alleviate the impact of climate change (McDermot and Elavarthi 2014). In this regard, the seasonal monitoring of biochemical parameters, such as nitrogen (N), phosphorus (P), and neutral detergent fibre (NDF) concentrations, will indicate forage quality and palatability.

Estimating biochemical parameters in rangelands is commonly done through expensive and time-consuming lab chemical approaches, which do not provide real-time data and have limited applications over extensive areas (Mutanga, Skidmore, and Prins 2004; Ramoelo et al. 2012). Remote sensing techniques offer a cost-effective potential for quantitatively assessing rangeland biochemical variables from property to regional scale. Over the past decades, remote sensing has been widely used to generate accurate information about vegetation biochemical parameters across an extensive area in near-real time (Ali et al. 2016). Its advantages, such as repetitiveness, low cost of data storage, universal coverage, and non-destructiveness during the mapping of biochemical parameters, make it preferable to all land users. However, despite the numerous advantages of remote sensing, several challenges associated with processing remote sensing data can impact the accuracy of estimated biochemical concentrations, such as N (Ayanu et al. 2012). These challenges include atmospheric interference, sensor calibration issues, and geometric distortions, all introducing uncertainties into the measurements.

Remote sensing technology's advancement has addressed some limitations in estimating vegetation biochemical parameters using conventional field data. For instance, Sentinel-2 (S2) has improved spectral bands with red-edge and offers higher spatial resolution, enabling more accurate estimation of biochemical parameters (Delegido et al. 2011; Parida and Kumari 2021). Some studies have even shown that utilizing red-edge bands and related indices can further enhance the estimation of biochemical concentrations in natural vegetation (Cho and Skidmore 2006; Clevers et al. 2002;

Darvishzadeh et al. 2008; Ramoelo et al. 2012). The red-edge refers to the section of rapid transformation in vegetation reflectance ranging between 600–800 nm, mainly influenced by the intense effects of spectral absorption in the red wavelengths and scattering in the near-infrared region (Ustin and Jacquemoud 2020). Within this context, the red edge is correlated with chlorophyll content, with limited saturation problems (Clevers et al. 2002; Croft et al. 2020).

Estimating the seasonal spatial distribution of biochemical parameters (N, P, and NDF) using Sentinel-1 (S1) and Sentinel-2 (S2) imageries was a focus of this study to address the paucity of literature on this. S1 and S2 data are freely available and have highly improved spectral and spatial resolution. S1 and S2 sensors were launched for diverse applications, although their primary aim was to monitor the dynamics and variation of land-use/land-cover and agrarian applications. These sensors provide repeated data with a shorter revisit period of 5–12 days with a high spatial resolution of 10–60 m (De Vroey et al. 2022; Veloso et al. 2017). S2 has an optical sensor that captures multispectral data in the visible, near-infrared, and shortwave infrared spectral regions vulnerable to cloud cover, but sensitive to the biochemical properties (such as chlorophyll content) (De Vroey et al. 2022; Shang et al. 2021). On the other hand, S1 uses a microwave range, and the backscatter is more sensitive to vegetation structure (Raab et al. 2020; Wachendorf, Fricke, and Möckel 2018) and is unaffected by clouds.

However, its application has not been extensively investigated in rangeland biochemical estimation studies compared to optical sensors due to its complexity (De Vroey et al. 2022). Hence, some studies have explored the combination of S1 and S2 data in vegetation monitoring, leveraging the strengths of both datasets to improve accuracy and reliability (Erinjery, Singh, and Kent 2018; Mahdianpari et al. 2019; Mahyoub et al. 2019). Data fusion of S1 and S2 sensors offers the benefit of improved spectral and textural information with the unique capabilities of each sensor (Cai, Lin, and Zhang 2019). Since each sensor has individual capabilities, combining them will help to assess different vegetation types (including extensive vegetation), under any ecological conditions; many studies have combined these sensors to obtain data under various environmental conditions. S1 and S2 integration could improve the estimation and monitoring of forage biochemical properties, with limited cloud interference. For instance, a study by Trivedi (2020), used S1 and S2 data to estimate chlorophyll content in arable land in Ghana and improved predictive power by 0.8. Similar study by Raab et al. (2020), also observed an increase in the predictive power (R^2 and RMSE between 0.72–0.79 and 1.70% − 2.29%) from the combination of S1 and S2 during estimating forage quality of semi-natural grasslands. Chatziantoniou et al. (2017), also suggested that high accuracy results were due to the synergistic use of S1 and S2 data in a study conducted in the wetlands of northern Greece. Additionally, Amankulova et al. (2024) and Wang et al. (2019), demonstrated that integrating S1 and S2 data can increase estimation accuracy for grassland productivity by 0.89 and 0.67, respectively. Integrating S1 and S2 remote sensing data can enhance the estimation of forage biochemical parameters in natural rangelands, effectively addressing the limitations inherent in single-sensor methodologies.

However, there is still a lack of scientific data and literature on using S1 and S2 data for biochemical estimations in rangelands (Meneghini 2019). Beyond limited studies on the integration of S1 and S2 for biochemical estimations, the sensitivity of S1 derived from South Africa has not been tested in the estimation of grass N, P and NDF in the mesic savanna.Therefore, the objectives of the study were to; firstly, to develop predictive seasonal models for the estimation of the spatial distribution of three biochemical parameters (N, P and NDF) concentrations in mesic rangelands using S1, S2 and integration of S1 and −2 data; and finally, to develop seasonal pooled models and mapping three nutrients. Understanding the spatial and temporal variability of biochemical parameters can reveal potential hotspots or areas of concern where nutrient management practices may need to be implemented to reduce the risk of rangeland degradation and improve overall forage quality. This information can also help land managers make informed decisions about stocking rates and grazing managements to ensure optimal forage utilization while maintaining the health and productivity of the rangeland.

2. Materials and methods

2.1. Study area

This study was conducted in two privately owned game reserves (Welgevonden and Hoogland) in the Waterberg Estate region, Limpopo Province, South Africa (Figure 1). The Waterberg region lies to the north of the Bushveld Basin, where it forms a highland area. The highest part of the area is in the south Kransberg in the southwest towers out above the Limpopo Plain at the foot of the cliff-like escarpment made up of Waterberg Sandstone. The topography of the study area ranges between 300 and 900 metres above Mean Sea Level. The region is predominantly warm to hot (mean minimum temperature is 12°C, mean maximum temperature is 44.90 °C) in summer and receives Mean Annual Precipitation (MAP) of 300–700 mm with mean annual evaporation of between 1750 and 1900 mm (Mundalamo 2019; Nesamvuni et al. 2003). Individually,

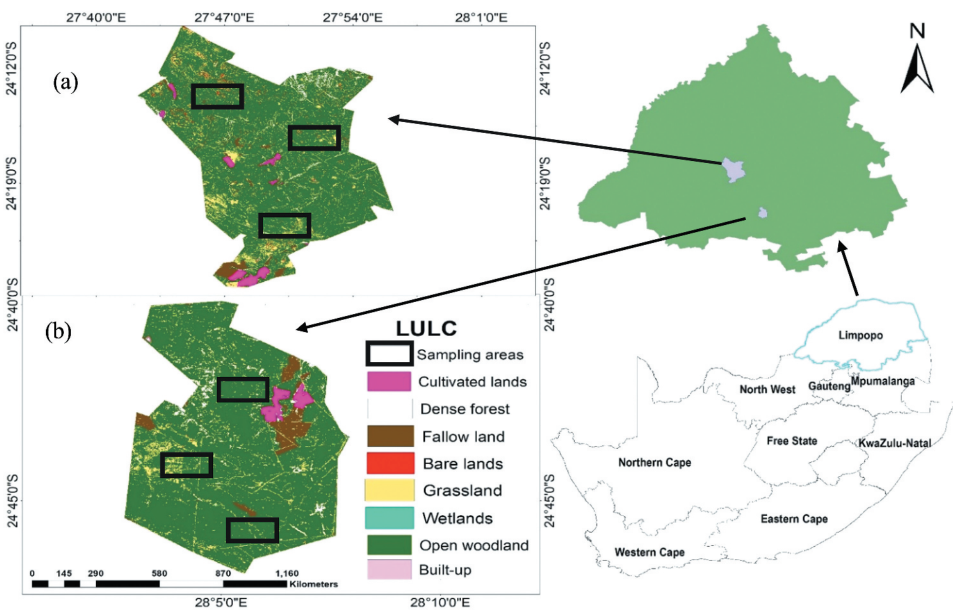

Figure 1. Illustration with two study sites in the waterberg region of Limpopo province, South Africa, Welgevonden(a) and Hoogland(b). The black square shows the sample areas.

Welgevonden Game Reserve is a privately owned reserve between the towns of Vaalwater and Lephalale that covers 37,500 hectares of South Africa's Waterberg Biosphere, Limpopo province, South Africa, at latitudes 24° 10′to 24° 25′ South and longitudes 27° 45′to 27° 56′ East. Welgevonden consists of two distinct vegetation types (sour bushveld and mixed bushveld) as classified by (Palmer and Ainslie 2006). At the same time, Hoogland is a protected game reserve located in the North-west of Bela-Bela town (24° 43′20.8′S 28°07′48.7′E), South of Waterberg Biosphere. Over the past 35 years until 2017, the Hoogland reserve was protected from wildfire (veld fire) with almost 200 plant species. The wildfire protection was done since the area is stated to be composed of fire-sensitive and fire-resistant species; therefore, the fire event normally destroys the fire-sensitive species as observed (Trollope 2011).

2.2. Field measurements

2.2.1. Sample collection

Field data collection was conducted from November 2020 to March 2022, encompassing three seasons: early summer (November-December 2020), winter (July-August 2021), and late summer (March 2022). Six areas with varying vegetation cover and standing biomass were randomly selected, three areas in each reserve. Within each area, transects were established using a combination of systematic placement and purposive sampling plots. Each transect was then subdivided into ten 30 × 30 m plots with homogeneous vegetation to capture variability. In each plot, a total of 10 quadrats of 1 m^2 (180 in total) were randomly located and shifted during each sampling event to prevent re-sampling. Then the fresh grass was clipped at 1 cm above the ground using scissors and oven dried at 70°C for 48 hours, then the dry matter was measured after 48 hours dried and converted into kilogram per hectare (Kg ha – 1), for further chemical analysis.

2.2.2. Laboratory analysis

Near-infrared spectroscopy (NIRS) is an analytical tool that uses a predetermined wavelength pattern of light (typically 800–2500 nm) to provide a full image of the organic composition of the investigated substance/material (Kilcast 2013). All the collected samples were analysed at the Af4rica laboratory at the University of Pretoria, following a strict and systematic protocol to ensure the most reliable results. Initially, the samples were dried in an oven at 70°C for 72 hours and then ground to a 1 mm particle size using a sieve. Subsequently, the milled samples were analysed for their chemical composition on a dry matter (DM) basis. Finally, each sample underwent a series of three experiments to derive its foliar biochemicals: Nitrogen (N), Phosphorus (P), and Neutral Detergent Fibre (NDF). These three biochemicals were then analysed using Near-Infrared Spectroscopy (NIRS).

2.2.2.1. Near-Infrared Spectroscopy (NIRS) analysis. NIRS is a non-invasive technique used to measure the percentage of saturated haemoglobin in a target tissue. It relies on two physical principles: differential absorption of near-infrared light and the modified Beer – Lambert law (Salido et al. 2017). NIRS devices use light in the near-infrared band (700–900 nm), which can penetrate skin, bone, and connective tissue. The chemical composition of the samples was analysed using the DA 7250 NIR analyser, a thirdgeneration diode array NIR instrument from PerkinElmer c, designed for quick analysis. The DA 7250 NIR Analyzer can accurately determine protein N, P, NDF, and many other parameters and can analyse samples in only 6 seconds. The instrument combines outstanding analytical accuracy with speed, ease of use, ruggedness, and versatility. It works in reflectance mode, using a moving grating monochromator to scan the region from 570 to 1850 nm with an interval of 2 nm (Bartzialis et al. 2021).

2.3. Image acquisition and pre-processing

This study utilized the recently launched constellations of Sentinel-1 (Synthetic Aperture Radar – SAR) and S2 (optical) from the Copernicus Open Access Hub (ESA) (Zhang et al. 2019). In this study, the remote sensing data sampling was obtained between the following dates November – January 2020 (early-summer), July-August 2021 (winter), and February – March 2022 (later-summer) corresponding to field data collection. S1 and S2 data were acquired from Google Earth Engine (https://code.earthengine.google.com. and https://code.earthengine.google.com) covering the study area each season. One scene was acquired, covering three growing seasons from 2020 to 2022 (three images). The Google Earth Engine (GEE) computer platform is a sophisticated tool widely used to process and interpret satellite images. GEE delivers a cloud-based infrastructure and a set of geospatial analytic tools that enable users to access and interpret large volumes of satellite data. This study used GEE to process the S1 and S2 data and calculate the metrics from bands (either VV or VH and S2 bands).

2.3.1. Sentinel-1 and Sentinel-2

S1, operating as a C-band Synthetic Aperture Radar (SAR) satellite, gives backscatter coefficients across various polarizations represented in decibels (dB). This dual-polarization spacecraft contributes essential Earth observation data, characterized by a revisit period of 12 days per individual satellite (Rutkowski, Canty, and Nielsen 2018). This study leveraged Ground Range Detected (GRD) scenes from S1, featuring Vertical – Vertical (VV) and Vertical-Horizontal (VH) bands at a 10 m resolution. Preprocessing of S1 images in Google Earth Engine (GEE) was conducted using the S1 toolbox level 1, encompassing tasks such as thermal noise removal, radiometric calibration, and terrain orthorectification (Onojeghuo et al. 2021). Acquisition of S1 image, obtained with a descending orbital pass, matched with the S2 imagery period, facilitated through the Google Earth Engine online platform.

The S2 data used in this study were acquired as surface reflectance products (L2A), processed using the sen2cor algorithm. Additional processing steps involved cloud and cloud shadow masking to enhance data quality and facilitate accurate analysis. S2, part of the European Space Agency's Copernicus Earth Observation programme, captures Earth imagery from a sun-synchronous orbit (Baumann et al. 2018; Zhang et al. 2019). The Level-2A data, which includes atmospherically adjusted surface reflectance, is accessible through Google Earth Engine (Zhang et al. 2019). To ensure data quality, S2 imagery with less than 10% cloud cover was acquired through Google Earth Engine. Cloud and cloud shadow masking were conducted using the quality assessment band (QA60) to identify and eliminate opaque and cirrus clouds (Nazarova, Martin, and Giuliani 2020). The

Table 1. Vegetation indices and bands used in this study.

Index	Bands	Reference
NDVI (Normalized Difference Vegetation Index)	red, nir	Rouse et al. (1974)
WDVI (Weighted Difference Vegetation Index)	red, nir	Richardson and Wiegand (1977)
RVI (Ratio Vegetation Index)	red, nir	Gorai et al. (2014)
MSAVI (Modified Soil Adjusted Vegetation Index)	red, nir	Qi et al. (1994)
MSAVI2 (Modified Soil Adjusted Vegetation Index 2)	red, nir	Qi et al. (1994)
NDREI1 (Normalized Difference red-edge Index 1)	Red-edge2, Red-edge1	Gitelson and Merzlyak (1994)
NDREI2 (Normalized Difference red-edge Index 2)	Red-edge3, Red-edge1	Gitelson and Merzlyak (1994)
MCARI (Modified Chlorophyll Absorption Ratio Index)	green, red, Red-edge1	Daughtry et al. (2000)
CLRE (Red-edge-band Chlorophyll Index)	Red-edge3, Red-edge1	Gitelson and Merzlyak (1994)
SATVI (Soil Adjusted Total Vegetation Index)	red, swir2, swir3	Marsett et al. (2006)
SLAVI (Specific Leaf Area Vegetation Index)	red, nir	Lymburner et al. (2000)
SR (Simple Ratio)	red, nir	Jordan (1969)
$SRRE1_{red\text{-}edge1}$ (Modified Simple Ratio+Red-edge1)	Red, nir, Red-edge1	Sims and Gamon (2002)
$SRRE2_{Red\text{-}edge2}$ (Modified Simple Ratio+Red-edge2)	Red, nir, Red-edge2	Sims and Gamon (2002)
$NDVIRE_{red\text{-}edge1}$(Modified Normalized Difference Vegetation Index +Red-edge1)	nir, Red-edge1	Gitelson and Merzlyak (1994)
$NDVIRE_{red\text{-}edge2}$ (Modified Normalized Difference Vegetation Index +Red-edge2)	nir, Red-edge2	Gitelson and Merzlyak (1994)

NB: Traditional indices = non-red-edge indices.

QA60 band is derived from the blue band and two short-wave infrared bands of the Sentinel-2 image (Chong et al. 2021). Subsequently, 10 reflectance bands were selected for analysis, comprising six at 20 m resolution and four at 10 m resolution. Sixteen vegetation indices (VIs) were developed for biochemical parameter assessment (see Table 1). One scene was acquired across study areas, covering three growing seasons from 2020 to 2022. Lastly, each season's individual datasets (field and remote sensing data) were pooled/merged into a single seasonal dataset (pooled dataset). The purpose of pooling datasets was to create complete seasonal models that can be used to estimate each biochemical parameter throughout the vegetation growing season in rangelands.

2.4. Data analysis

All data analyses were computed using the R-programme, version 4.1.0. (R Core Team, 2021). Descriptive statistics, including mean, minimum (Min), maximum (Max), and coefficient of variation (CV), were calculated to understand the overall forage quality in the study area. The differences in three chemical components and spectral absorption features between seasons and study areas were investigated by computing the analysis of variance (ANOVA) to test whether there was any significant difference between seasonal foliar N, P, and NDF concentrations throughout the study areas in the detection of rangeland forage quality. Pearson's correlation analysis was conducted before and after predictions between chemical composition and the raw reflectance of samples to identify the most suitable indicators for estimating chemical components from both laboratory and field conditions. All variables selected were found to be sensitive to the concentrations of N, P, and NDF. The relationships were plotted against spectral regions for comparison purposes. The observed biochemical data and the accumulated absorption data were set aside for validation, and stepwise regression analysis was applied to develop a model for predicting biochemical parameters using field-measured accumulated absorption derived from reflectance.

2.4.1. Development of biochemical parameters predictive models

Random decision forest regression is a statistical method used in ecology for predicting the biophysical properties of vegetation. This method is a non-linear ensemble approach that generates and averages multiple randomized, de-correlated decisions for regression purposes (Hastie et al. 2009). One of the key advantages of this method for ecological studies is the ability to easily include or exclude predictors based on data availability and user requirements. Another benefit is the possibility of including continuous and categorical predictors, such as land use information. Additionally, this method requires fewer user-specified parameters and reduces the risk of overfitting, as well as automatically calculating a variable importance score that assesses the contribution of individual predictors to the final models.

2.4.2. Accuracy assessment

The developed regression model was validated using the cross-validation method (implemented in the caret package and VSURF package in R ×643.4.0) to determine the coefficient of determination (R^2) as a measure of goodness-of-fit, as well as the root mean square error (RMSE), relative RMSE (%), and mean absolute value of errors (MAE) to assess accuracy. The model's performance was then assessed by comparing the differences in R^2 and RMSE between the estimated and measured values of vegetation biophysical properties. Higher R^2 values and lower RMSE, MAE and bias values corresponded to higher precision and accuracy of the model for predicting vegetation biophysical properties. Equations (1) to (5) were used to calculate R^2, RMSE, relative RMSE, MAE, and bias respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (yi - \tilde{y}i)^2}{\sum_{i=1}^{n} (yi - \bar{y})^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (yi - \tilde{y}i)^2} \tag{2}$$

$$\mathrm{RRMSE} = \sqrt{\frac{\frac{1}{n}\sum_{i=1}^{n} (yi - \tilde{y}i)^2}{\sum_{i=1}^{n} (\tilde{y}i)^2}} \tag{3}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid \mathrm{y}i - \tilde{y}i \mid \tag{4}$$

$$\mathrm{Bias} = \frac{1}{n}\sum_{i=1}^{n} (yi - \tilde{y}i) \tag{5}$$

Where: y_i is the observed/measured value, $\tilde{y}_i$ is the predicted value and $\bar{y}$ is the mean of the measured values. *n* = sample size.

Table 2. A total of 15 model scenarios were developed using bands and different indices (from S1, S2 and integration).

Model	S1 + S2
1	Bands + Red-edge + Traditional indices
2	Bands+ Red-edge
3	Bands + Traditional indices
4	Red-edge + Traditional indices
5	Bands
6	Red-edge
7	Traditional
8	VH + VV
9	Bands + Red-edge + Traditional indices + VH/VV
10	Bands+ Red-edge + VH/VV
11	Red-edge + Traditional indices + VH/VV
12	Bands+ Traditional indices + VH/VV
13	Bands + VH/VV
14	Red-edge + VH/VV
15	Traditional + VH/VV

NB: Traditional indices = non-red-edge indices.

2.4.3. Random Forest (RF)

RF is a machine learning algorithm developed to improve vegetation classification and regression methods. This study utilized RF to estimate forage N,P, and NDF using unoptimized and optimized combinations of vegetation indices (VIs) and spectral bands, as shown in Table 2. RF is a decision tree-based collective method that is widely implemented for classification and regression problems (accuracy importance measure, Gini importance, and a number of times each variable is selected) (Breiman 2001). The method utilizes feature randomness and bagging when constructing each individual tree. Moreover, it is suitable for analysing high-dimensional data and robust to nonlinear and unbalanced data (Venables, Smith, and Core Team 2015). The RF algorithm has several key parameters, including the number of predictors (mtry), which depends on the square root of the total number of predictors used, and default values of two for the minimal size of the terminal nodes (node size) and 500 for the number of regressions. In this study, to obtain high accuracy, the RF model was used according to the error rate reported by (Ismail et al. 2010). Then the seasonal pooled data operations were performed for forage N, P, and NDF modelling and mapping, variable selection, and model accuracy assessment. The final model (best model) was selected when the prediction error was the lowest.

Table 3. Summary of the seasonal chemical analysis throughout the study area.

Nnutrient	Min	Max	Median	CV (%)
Nitrogen (N%)	0.35	1.57	0.85	31.38
Phosphorus (P%)	0.1	0.27	0.19	22.35
Neutral detergent fibre (NDF%)	55.6	77.48	68.22	7.08

CV = Coefficient of variation (%).

3. Results

3.1. Descriptive statistics

Table 3 presents the findings of the biochemical analysis conducted on the samples collected in the field during the growing season. The seasonal variation of biochemical parameters such as N, P, and NDF across the study areas was moderate, with a coefficient of variation (CV) ranging from 7 to 31%, respectively.

3.2. Seasonal biochemical variables predictive models

The results demonstrate the successful prediction of field-collected biochemical parameters throughout the growing season using RF models, as shown in Table 4. In mesic tropical rangelands, the RF models produce optimal seasonal estimations of all biochemical parameters, with an overall seasonal coefficient of determination (R^2) ranging from the lowest of 0.34 (for NDF during E.S from S1) to the highest of 0.74 (for P during L.S from S1+S2).On the other hand, RMSE and RRMSE ranged between 0.01–4.26 and 4.68–14.67, respectively, with MAE < 10 in all parameters throughout the seasons, indicating the high accuracy and reliability of the prediction models. The combined use of S1 and S2 data significantly improves estimation accuracy for all seasonal biochemical parameters, with coefficients of determination and relative root mean square errors ($R^2 = 0.61–0.74$; RRMSE = 2.26–14.67), specifical. However, this study also shows the effect of seasonality in predicting biochemical parameters and variable selection, with L.S producing the most accurate estimations across study areas, followed by winter and E.S, separately. Additionally, the most effective variables within the RF models for seasonal biochemical predictions were analysed, with the red-edge-based parameters (such as CARI and CLRE) being highly selected in all seasons. Notably, variable selection is during the late summer season had an increased selection of red-edge-based parameters, while S1 parameters were also active and selected for biochemical parameter predictions. The bands were mostly selected during the estimation of P followed by NDF and N with the least selection throughout the seasons.

3.3. Seasonal biochemicals pooled predictive models

The seasonal biochemical pooled models were developed from RF using S1, S2 and their combined data. This was done to create a universal model that can be effectively used throughout the growing season for natural rangeland biochemical predictions. Since the RF model combined with ancillary data produced the best accuracies for predicting biochemical parameters (N, P and NDF%). This section first focuses on the correlation of the most important variables selected within the biochemical-based models (from Table 5) and then looks at the best-performing seasonal models and maps the distribution of each variable. Figure 2 shows that all selected predictive parameters presented relatively strong significant correlations among each other and were highly active for biochemical parameters prediction, hence they produced correlation; the correlation coefficients R^2 were all > 0.40. All 11 selected predictor variables show a positive

Table 4. Seasonal predictive models of biochemical parameters using remote sensing data (Table 4 **a** = N %; **b** = P % and **c** = NDF %).

Season	Scenarios	Variable importance	R^2	RMSE	RRMSE	MAE
a. N % (DM) based seasonal models.						
	S1	VV	0.37	0.13	10.11	0.11
E.S	S2	NDVIRE2, NDVIRE1, SRRE1, CLRE, B5	0.48	0.12	7.49	0.10
	S1+S2	NDVIRE2, NDVIRE1, CLRE	0.57	0.11	7.35	0.10
	S1	VH, VV	0.39	0.13	14.67	0.11
W	S2	NDVIRE1, B6, B7, SRRE1, B5, B8A, SR	0.55	0.12	13.65	0.10
	S1+S2	NDVIRE1, SRRE2, CLRE, MCARI	0.63	0.12	13.43	0.11
	S1	VV, VH	0.48	0.14	10.01	0.11
L.S	S2	MCARI, NDVIRE1, B8	0.67	0.15	9.98	0.12
	S1+S2	MCARI, B8, NDVIRE1, CLRE	0.70	0.14	9.86	0.11
b. P % (DM) based seasonal models.						
	S1	VV	0.41	0.02	5.54	0.01
E. S	S2	B6, B5, B7, B8	0.66	0.01	5.01	0.02
	S1+S2	B5, B8, B7, NDREI1, MCARI	0.60	0.02	4.68	0.01
	S1	VV, VH	0.50	0.04	12.48	0.03
W	S2	MCARI, CLRE, B12, B4	0.68	0.03	11.48	0.26
	S1+S2	B4, B12, B7, VV, B8A	0.62	0.04	10.05	0.30
	S1	VV, VH	0.57	0.02	6.87	0.02
L.S	S2	MCARI, B3, B12, B2	0.66	0.02	6.98	0.03
	S1+S2	MCARI, B3, VV, B12, SRRE1	0.74	0.02	6.88	0.12
c. NDF % (DM) based seasonal models.						
	S1	VH	0.34	2.36	2.29	1.87
E. S	S2	SRRE1, NDVIRE2, SRRE2, NDVIRE	0.51	2.43	2.51	1.65
	S1+S2	SRRE1, SRRE2, NDVIRE2, VH, CLRE	0.50	2.38	2.26	1.92
	S1	VV, VH	0.46	3.75	3.67	3.14
W	S2	B2, MCARI, SLAVI	0.63	3.33	3.41	2.79
	S1+S2	B2, SLAVI, B8, VV, MCARI	0.68	3.01	3.35	3.02
	S1	VV, VH	0.50	4.19	4.95	3.42
L.S	S2	B2, B5, B3, MCARI, B8, CLRE	0.70	3.99	4.91	3.28
	S1+S2	NDVIRE, CLRE, VV, MCARI,	0.72	4.26	4.84	3.50

Early summer (E.S); Winter(W); Later summer (L.S).

Table 5. Performance of pooled-based biochemical models achieved from S1 and S2 data using random forest modelling algorithm.

Nutrient	Scenarios	Selected variables	R^2	RMSE	RRMSE	MAE	Bias
	S1	VV,VH	0.67	0.15	3.54	0.12	−0.011
N	S2	B7, B5, MCARI, NDREI2, B8A, SRRE1	0.70	0.16	4.06	0.13	−0.003
	S1+S2	B6, B7, MCARI, CLRE, NDREI1, VV	0.76	0.13	4.16	0.12	−0.001
	S1	VV,VH	0.61	0.03	9.65	0.12	−0.0021
P	S2	B12, B5, B4, SATVI, NDVIRE1	0.70	0.03	7.81	0.02	−0.0018
	S1+S2	SRRE1, VV, VH, CLRE, MCARI	0.78	0.04	8.58	0.03	−0.0002
	S1	VV	0.56	2.67	3.72	1.76	−0.055
NDF	S2	B7, B6, B8A, MCARI, CLRE, SATVI, B2	0.63	2.72	3.72	1.84	−0.043
	S1+S2	B6, B7, B8, B4, MCARI, CLRE, VV, SLAVI	0.71	2.52	3.59	1.66	−0.042

correlation with nitrogen, while out of 11 and 10 selected for P and NDF, only 9 and 2 show a positive correlation, respectively.

3.3.1. *Visual-spatial distribution of biochemical parameters in ecological context*

Nonetheless, through the evaluation of the accuracy comparison of R^2, RRMSE, MAE, and bias metrics, the models for the integration of S1 and S2 were identified as the best-performing models. Hence, further spatial distribution analysis of biochemical parameters across the seasons was conducted using these models (refer to Table 5). All the biochemical pooled models generated R^2 (>0.50), RRMSE < 10%, and low negative bias (from

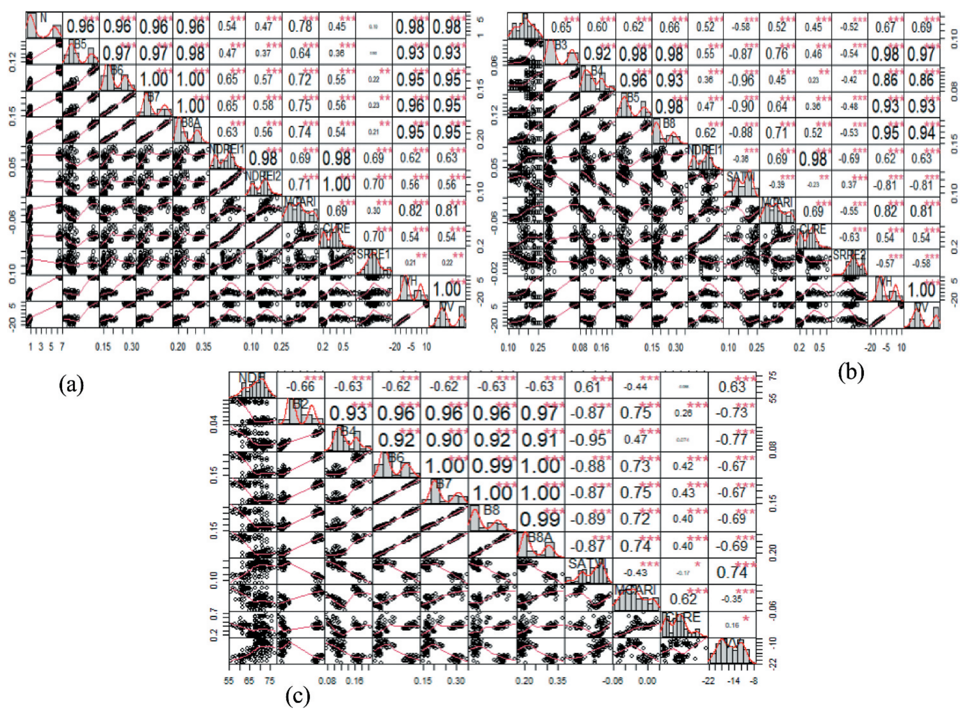

Figure 2. Correlation matrix between the selected variables for best models and biochemical parameters (from Table 4). *** indicates regression significance at a p<0.001. a, b and c best models for Nitrogen; Phosphorus and Neutral detergent fibre, respectively.

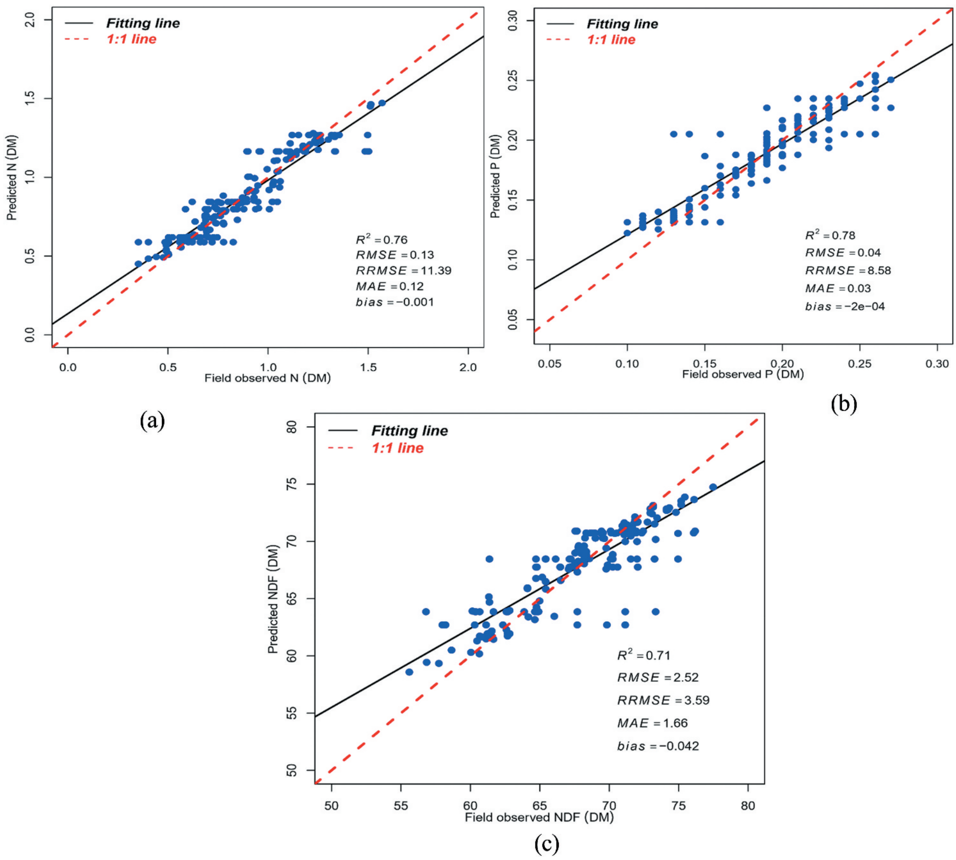

Figure 3. Scatterplots of the estimated biochemical and observed biochemical parameters throughout the season; a, b and c: scatterplot for N% (DM), P% (DM) and NDF% (DM) concentrations, respectively.

−0.0002 to −0.055) which signifies a negligible error. The scatter plot depicted in Figure 2 elucidates the pooled seasonal biochemical predictive models.

Figure 3 represents the correlation between the observed and predicted seasonal pooled values of biochemical parameters. These models were formulated by integrating data from integration S1 and S2 across all biochemical parameters. On the other hand, Figure 4 illustrates the realistic patterns of seasonal pooled biochemical concentrations across the research areas. The variability of all biochemical parameters is more pronounced in high slope regions than in flat slope areas. However, there were no significant variations observed in all biochemical parameters within the study areas, as shown in Figure 4.

Furthermore, Table 6 presents the statistical results of seasonal biochemical parameters across the research areas. Employing an analysis of variance (ANOVA), the findings suggest that there was no substantial variation ($p > 0.05$) among the study regions, despite the fact that HG exhibited significantly higher concentrations of all the biochemical parameters throughout the seasons. Meanwhile, the seasonal fluctuations displayed a significant influence on the distribution of all the biochemical parameters across the study areas. Specifically, nitrogen and phosphorus concentrations were highest in late

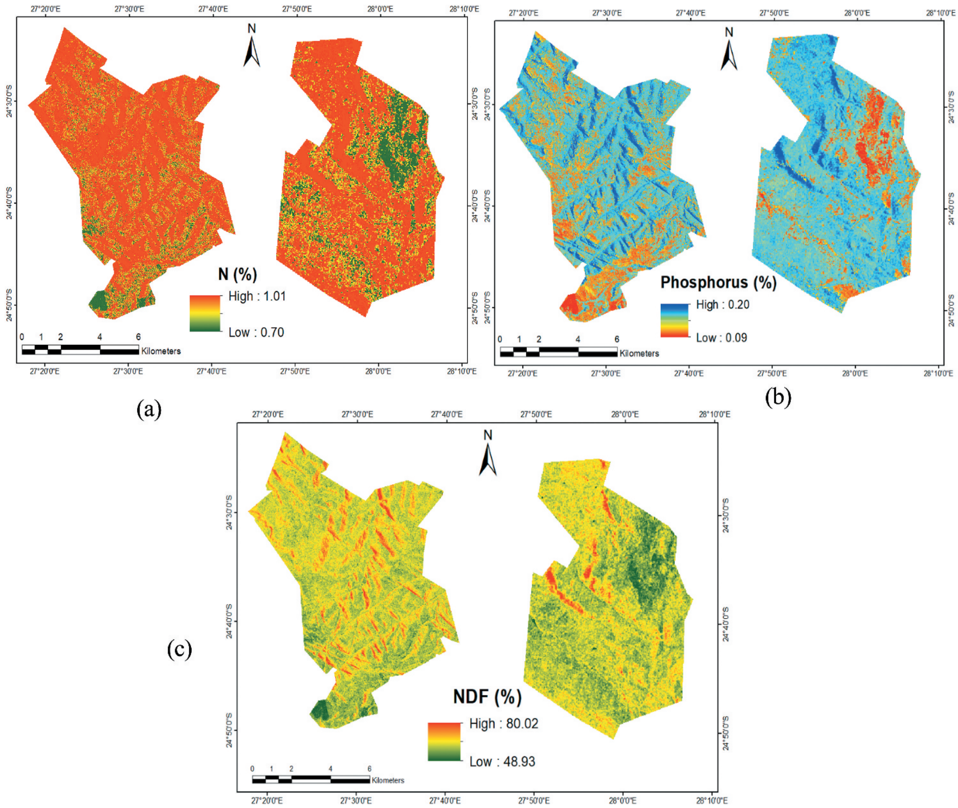

Figure 4. Spatial distribution of the pooled seasonal biochemical parameters concentrations derived from the field data-based models applied to the integration of S1 and S2 images. a, b and c distribution of seasonal pooled nitrogen, phosphorus and neutral detergent fibre concentrations throughout the study areas, respectively.

Table 6. The analysis of influence seasonality in N%, P% and NDF% concentrations throughout the study areas.

		Chemical elements(%DM)								
			N			P			NDF	
Area	Season	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
WV	E. S	0.84	0.12	14.83	0.18	2.15	3.03	70.96	0.01	7.01
	W	0.60	0.14	23.67	0.13	0.011	9.26	70.58	4.44	6.29
	L.S	1.08	0.12	11.33	0.21	0.02	7.47	62.01	2.53	4.08
	S	***	ns	***	*	**	***	**	***	**
HG	E. S	0.95	0.11	11.43	0.13	0.04	29.78	72.06	4.33	6.01
	W	0.64	0.10	14.90	0.19	0.05	24.77	67.59	2.14	3.17
	L.S	1.28	0.12	9.34	0.24	0.02	8.16	65.58	4.79	7.66
	S	***	ns	***	**	ns	***	**	***	***

Significance levels of tests(S): 0.01 = ***,0.05 = **,0.1 = *,ns = non-significant. Coefficient of Variation (CV); Standard Deviation (SD); Early summer (E.S); Winter(W); Later summer (L.S); Welgevonden (WV) and Hoogland (HG).

summer, followed by early summer and winter, respectively. Conversely, early summer exhibited a high concentration of NDF, whereas the winter and late-summer had the least concentration of NDF across the research areas.

4. Discussion

4.1. Foliar biochemical concentration

The seasonal variation of N, P, and NDF across the study areas was characterized by low to moderate coefficients of variation (CVs) ranging from 7% to 31%. The median values for N, P, and NDF were 0.85, 0.19, and 68.22, respectively, which are considered reasonable for grasses according to previous research by (Knox et al. 2012; Ramoelo and Cho 2018). Seasonal concentrations of N, P, and NDF were used as indicators of forage quality throughout the study areas. The results of this study show that the distribution and occurrence of these biochemical parameters are influenced by various factors such as ecological conditions, slope, and disturbances namely: wildfires in heterogeneous vegetation, as observed by (Venter, Hawkins, and Cramer 2017). A comprehensive understanding of the distribution and occurrence of these biochemical parameters is crucial for various ecological and environmental applications, including nutrient mapping and understanding the effects of land use on rangeland processes (R. Wang and Gamon 2019). However, according to Schmidt and Skidmore (2001) and Chapin (1980), the importance of various grass nutrients cannot be overstated, as diverse grass species exhibit variations in nutrient storage and transportation. Therefore, it is necessary to consider these factors and account for them in different seasons.

4.2. Seasonal biochemical variables predictive models

The integration of data from multiple sensors, such as S1 and S2, has emerged as a highly effective approach for precision ecological monitoring in rangelands (Bernardi et al. 2016). This study highlights the ecological significance of connecting the combined potential of these sensors to create detailed maps of seasonal biochemical parameters. By applying random forest (RF) models, the interaction between S1 and S2 datasets enables accurate estimation and prediction of nutrient distribution and occurrence, providing comprehensive insights into the intricate fluctuations of seasonal rangeland conditions (Fernández-Habas et al. 2021, Raab et al., 2020; L. Wang et al. 2020). The collaborative nature of S1 and S2 data significantly improves prediction precision due to their comprehensive assessment of vegetation attributes and ecological dynamics, particularly in regions characterized by diverse vegetation and complex ecological interactions. Furthermore, the integration of S1 and S2 data integration excels, particularly during the late-summer season, due to the season's unique attributes, such as moisture effects, photosynthetic pigments, and water absorption elements in foliage spectra (Kokaly and Clark 1999; Ramoelo et al. 2014). Notably, the integration of S1 and S2 consistently outperforms individual sensors, highlighting the essential role of red-edge parameters and near-infrared (NIR) bands in attaining heightened precision and variability in predicting biochemical parameters (Clevers et al. 2002; Kokaly et al. 2009; Ramoelo et al. 2015; Verrelst et al. 2012). These findings emphasize the ecological significance of factors such as soil composition, topography, vegetation cover, phenological stages, land use, and climatic variations in influencing the spatial distribution of nutrients within rangelands, underlining the need for comprehensive visual analysis to holistically understand rangeland conditions (A. A. Gitelson et al. 2003; F. Wang, Wang, and He 2021; Weltz et al. 2003).

4.3. Seasonal biochemicals pooled predictive models

In this study, the seasonal pooled models employed for predicting the three crucial nutrients (N, P, and NDF) displayed robust predictive capabilities, with R^2 values exceeding 0.50 and RRMSE values below 10%. The integration of S1 and S2 data consistently outperformed individual sensors, with a notable preference for red-edge-based bands and indices for accurate estimation. These findings were then utilized to create scatterplots illustrating the seasonal distribution of these nutrients, followed by the production of maps depicting their spatial distribution across the study areas. Interestingly, despite the seasonality and ecological complexities known to influence nutrient distribution, the visual representation of N, P, and NDF concentrations showed slight variation across the sites. Nonetheless, as highlighted in prior research, factors like seasonality, ecological conditions, and anthropogenic activities, including fire occurrences, have significant impacts on the spatial distribution and occurrence of these nutrients (Potts et al. 2020; Ramoelo and Cho 2018). Specifically, the influence of slope degree on the seasonal distribution and occurrence of these biochemical parameters appeared as a significant factor in this study, while the slope aspect exhibited no significant effect. These findings align with observations that slope degree can substantially impact the distribution and occurrence of forage parameters in rangelands, with higher concentrations often found in bottomlands and lower concentrations in highlands (Grant and Scholes 2006; Ramoelo and Cho 2018). These ecological nuances emphasize the importance of considering terrain characteristics and ecological factors in rangeland management and nutrient distribution assessments (Auslander, Nevo, and Inbar 2003; Gutiérrez-Jurado and Vivoni 2013).

4.3.1. Explaining spatial distribution of biochemical parameters in ecological context

This study has revealed that the high forage quality observed in the high slopes of rangelands can be attributed to the presence of numerous highly palatable grass species, which in turn result in higher nutrient content (see Table 7 and Figure 5). Research has shown that high slopes create a stressful environment for plants, potentially triggering the production of secondary metabolites like phenolic compounds, alkaloids, and tannins in the grasses. These compounds can enhance forage nutritional quality by mitigating the negative impact of grass fibre and boosting protein content and digestibility (Abdelal 2021; Ramachandra Rao and Ravishankar 2002). Another contributing factor could be the higher rainfall occurrence in such mesic/wet rangelands, leading to elevated moisture levels in both soil and vegetation. This increased moisture content can alter soil chemistry, potentially increasing soil acidity due to the leaching of essential minerals and encouraging the growth of acid-producing microorganisms. These changes can promote soil acidification and the proliferation of highly palatable plant species (Tian and Niu 2015). Moreover, higher slopes are often associated with a more efficient hydrologic cycle, reducing waterlogging compared to low-lying areas. This fosters a conducive

Table 7. Cross-correlations between slope type and biochemical parameter throughout the study areas.

Slope type vs. Biochemical	R	P<0.05
SD vs. Nitrogen (N)	0.28	Yes
SD vs. Phosphorus (P)	0.35	Yes
SD vs. Neutral detergent fibre (NDF)	0.42	Yes
SA vs. Nitrogen (N)	−0.01	No
SA vs. Phosphorus (P)	−0.02	No
SA vs. Neutral detergent fibre (NDF)	−0.09	No

SD = Slope degrees; SA = Slope Aspect and *R* = coefficient of correlation.

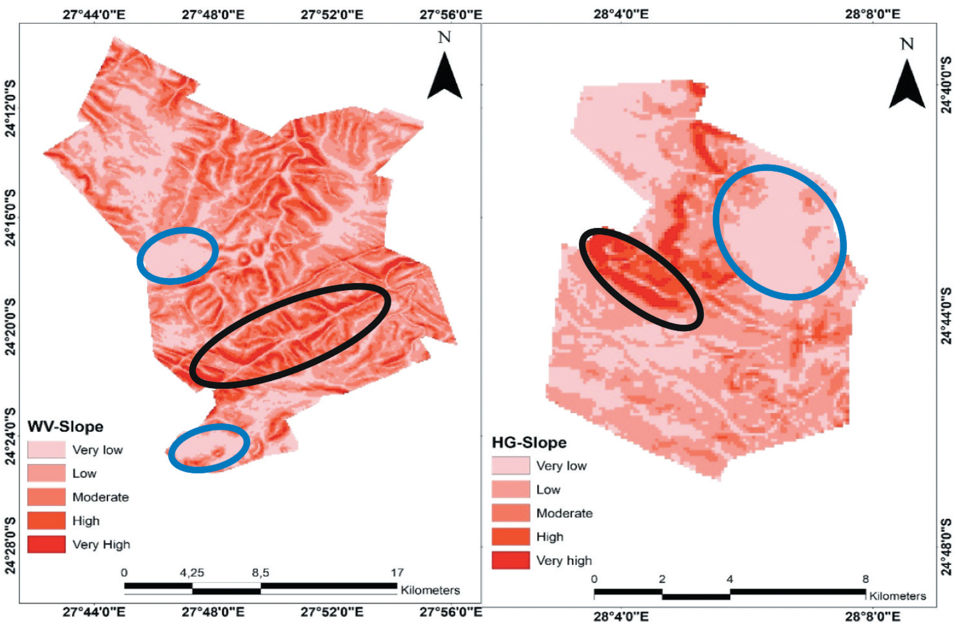

Figure 5. Visual representation of slop of the study areas corresponding to the distribution of biochemical parameters; the Black circle represent most notable high slope, and Blue for the low slope. The low slope (blue circle) shows a relatively low concentration and increases the concentrations with an increase in slope (black circle) in all three nutrients throughout the study areas.

environment for soil microbes and nutrient availability, ultimately contributing to higher forage quality (Frey et al. 2006).

Additionally, this study found that high seasonal concentrations of the three nutrients in the HG (high slope) area were linked to the occurrence of wildfires. These findings align with previous research highlighting the significant impact of fire on forage quality in natural rangelands, often resulting in improved forage quality. Fires create favourable conditions for palatable grass species with high grazing value while reducing the presence of unpalatable species (Auslander, Nevo, and Inbar 2003; Ramoelo and Cho 2018; Thapa et al. 2022; Trollope 2011; Vera-Velez et al. 2023). However, it's noteworthy that seasonal dynamics exhibited significant variations among the nutrients, with the late summer season consistently featuring the highest concentrations of N and P and the lowest levels of NDF across the study areas. These variations highlight the complex relationship of factors influencing nutrient distribution and occurrence, which can differ for each nutrient across different seasons (Manolikaki et al. 2022).

4.3.1.1. Nitrogen(N). In an ecological context, N is a crucial element that measures the quality of rangeland and remains a limiting factor for agricultural production and ecological functioning. It is also an excellent indicator of rangeland productivity as it explains seasonal photosynthetic efficiency clearly (Ramoelo and Cho 2018). The distribution and occurrence of N are typically affected by several factors, such as species, growth stage, ecological conditions (such as seasonality and soil fertility), and management interventions (e.g. fire and grazing). In this regard, seasonality significantly influences the distribution and occurrence of N concentration, with notable variations occurring during later summer, followed by early summer and winter with the least concentration. These variations are associated with the fact that during summer, particularly later summer in these types of rangelands, there is high moisture content availability (both vegetation and soil), creating a favourable environment for soil microbial processes (bacteria and fungi). These processes are essential for the mineralization of nitrogen, which causes high availability of inorganic materials to be easily absorbed by plants, whereas during winter, these processes slow down due to low temperatures, resulting in low N concentration (Khangura et al. 2023). The results of this study also correspond with other studies that show a decrease in N as grasses mature due to the development of reproductive tillers with more proportions of cellulose and lignin (Gelley, Nave, and Bates 2016; Pontes et al. 2007). Hence, during early-summer in this study, there were lower N concentrations compared to later summer, associated with the fact that the grass was still under stress from winter conditions, with high tiller counts as defence mechanisms (Nie and Norton 2009).

4.3.1.2. Phosphorus(P). Forage P is widely recognized as a critical factor influencing animal grazing and feeding behaviour and, consequently, the quality of rangelands (Ramoelo et al. 2013). According to KavanovÁ et al. (2006), P plays a pivotal role in vegetation growth and contributes to the flexibility of plant communities throughout the changing seasons. However, the distribution and occurrence of phosphorus are intricately linked to the metabolic activities of vegetation. Therefore, comprehending the seasonal variations in phosphorus distribution is paramount for the effective management and monitoring of natural rangelands. Regular monitoring of phosphorus levels can pinpoint areas where additional management interventions may be needed to mitigate the risk of vegetation loss in these ecosystems. This study underscores the substantial impact of seasonality on P distribution, with late-summer exhibiting high P concentration production, followed by early summer and winter, which recorded comparatively lower levels. These findings align with research by Gao et al. (2020), indicating slightly higher P concentrations in grass species during the rainy season compared to the dry season. Furthermore, changes in species composition and soil nutrient availability can influence rangeland quality, particularly after disturbances like wildfires or grazing (Ferwerda et al. 2006). Schachtman et al. (1998), have highlighted P concentration shifting towards the root as vegetation ages, with some phosphorus preserved in older leaves and transferred to new shoots or leaves during the early growing season (early summer). These findings corroborate observations by Grant and Scholes (2006), who noted very low P concentrations at the end of the dry season, often falling below the maintenance requirements for grazing animals. Regular monitoring of P levels remains crucial for identifying areas requiring targeted management actions to safeguard vegetation in rangeland ecosystems.

4.3.1.3. Neutral Detergent Fibre (NDF). Fibre is a crucial nutritional component influenced by both biological variables and chemical composition (Van Soest, Robertson, and Lewis 1991). Among the essential elements of a forage diet used to assess the overall forage quality of herbivorous animals, including wildlife, is fibre content, such as NDF. However, studies by Erkovan et al. (2009) and Lacefield et al. (1999), have noted the significant impact of vegetation maturity, the proportion of grass mechanisms, and seasonal dynamics on the distribution and occurrence of NDF in natural rangelands. NDF concentration gradually declines during the first stages of growth due to stem elongation. These observations align with the results of this study, which showed relatively high NDF during early summer and low NDF in later summer. The high concentration of NDF during early summer is attributed to grasses still possessing the morphological characteristics that protect them during winter, which decline from mid to later summer. Additionally, our results show low NDF during later summer when there is high rainfall, which is consistent with the observations of (Moore and Jung 2001). Areas with increased soil moisture content tend to have lower overall fibre content, including NDF, as forage vegetation growing under high moisture content conditions is often stunted, resulting in a lower concentration of fibre elements (Buscaglia et al. 1994).

5. Conclusion

This study aimed to map the spatial distribution of seasonal biochemical parameters and estimate rangeland production by utilizing S1, S2, and the integration of S1 and S2 multi-temporal data. The quality of rangelands can be assessed and monitored using RF and the integration of S1 and S2 data. The red-edge parameters can indicate the levels of three foliage nutrients: N, P, and NDF. Seasonal concentrations of these nutrients were related to different predictor variables across the study areas, with red-edge variables strongly associated with their distributions. The study results demonstrated that models derived from the integration of S1 and S2 data effectively predicted all three nutrients. Furthermore, these models can be applicability to any rangeland type for estimation of forage nutrient throughout the entire season. However, the seasonality of the nutrients varied, and several individual factors, such as slope, ecological conditions, and management interventions, were found to influence their occurrence. The study's findings offer an economical and effective tool for rangeland users, including farmers, resource managers, and decision-makers, to monitor rangeland quality throughout the season in mesic tropical rangelands. The study also suggested that later-summer is the ideal time for forage to be harvested or grazed since the forage's nutritive concentrations in rangelands meet the production system's goals. Future research could build on this study's results by applying this knowledge to several datasets, expanding the study to different rangelands, and examining other ecological factors, such as slope altitude, to detect foliar fibre biochemicals. Ultimately, future research could scale up the products obtained in this study for multispectral use.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Authors' contributions

Rapiya Monde took the lead in writing the article. All authors offered significant feedback and helped structure the study, analysis and article. Abel Ramoelo and Wayne Truter have made a significant contribution to the idea of the article, the acquisition and interpretation of data for the article. All authors reviewed the manuscript.

Availability of data and material

All the Sentinel data are free of cost and are in the open domain, and field data port the published claims and fulfil with field requirements.

Declarations

Consent for publication: The authors unanimously agreed to publish this article. All authors have read, understood, and have complied as applicable with the statement on 'Ethical responsibilities of Authors'.

References

Abdelal, Q. 2021. "Floating PV; an Assessment of Water Quality and Evaporation Reduction in Semi-Arid Regions." *International Journal of Low-Carbon Technologies* 16 (3): 732–739. https://doi.org/10.1093/ijlct/ctab001.

Ali, I., F. Cawkwell, E. Dwyer, B. Barrett, and S. Green. 2016. "Satellite Remote Sensing of Grasslands: From Observation to Management." *Journal of Plant Ecology* 9 (6): 649–671. https://doi.org/10.1093/jpe/rtw005.

Alkemade, R., R. S. Reid, M. van den Berg, J. de Leeuw, and M. Jeuken. 2013. "Assessing the Impacts of Livestock Production on Biodiversity in Rangeland Ecosystems." *Proceedings of the National Academy of Sciences* 110 (52): 20900–20905. https://doi.org/10.1073/pnas.1011013108.

Amankulova, K., N. Farmonov, K. Omonov, M. Abdurakhimova, and L. Mucsi. 2024. "Integrating the Sentinel-1, Sentinel-2 and Topographic Data into Soybean Yield Modelling Using Machine Learning." *Advances in Space Research* 73 (8): 4052–4066. https://doi.org/10.1016/j.asr.2024.01.040.

Auslander, M., E. Nevo, and M. Inbar. 2003. "The Effects of Slope Orientation on Plant Growth, Developmental Instability and Susceptibility to Herbivores." *Journal of Arid Environments* 55 (3): 405–416. https://doi.org/10.1016/S0140-1963(02)00281-1.

Ayanu, Y. Z., C. Conrad, T. Nauss, M. Wegmann, and T. Koellner. 2012. "Quantifying and Mapping Ecosystem Services Supplies and Demands: A Review of Remote Sensing Applications." *Environmental Science & Technology* 46 (16): 8529–8541. https://doi.org/10.1021/es300157u.

Bartzialis, D., K. D. Giannoulis, E. Skoufogianni, G. Charvalas, and N. G. Danalatos. 2021. *Nitrogen fertilization's Effect on the Quality Characteristics of Various Sorghum Varieties*. http://agrosym.ues.rs.ba/article/showpdf/BOOK_OF_PROCEEDINGS_2021_FINAL.pdf.

Baumann, M., C. Levers, L. Macchi, H. Bluhm, B. Waske, N. I. Gasparri, and T. Kuemmerle. 2018. "Mapping Continuous Fields of Tree and Shrub Cover Across the Gran Chaco Using Landsat 8 and Sentinel-1 Data." *Remote Sensing of Environment* 216:201–211. https://doi.org/10.1016/j.rse.2018.06.044.

Bernardi, R. E., M. Holmgren, M. Arim, and M. Scheffer. 2016. "Why Are Forests so Scarce in Subtropical South America? The Shaping Roles of Climate, Fire and Livestock." *Forest Ecology and Management* 363:212–217. https://doi.org/10.1016/j.foreco.2015.12.032.

Breiman, L. 2001. "Random Forests." *Machine Learning* 45 (1): 5–32. https://doi.org/10.1023/A:1010933404324.

Buscaglia, H. J., H. M. Van Es, L. D. Geohring, H. C. A. M. Vermeulen, G. W. Fick, and R. F. Lucey. 1994. "Alfalfa Yield and Quality Are Affected by Soil Hydrologic Conditions." *Agronomy Journal* 86 (3): 535–542. https://doi.org/10.2134/agronj1994.00021962008600030015x.

Cai, Y., H. Lin, and M. Zhang. 2019. "Mapping Paddy Rice by the Object-Based Random Forest Method Using Time Series Sentinel-1/sentinel-2 Data." *Advances in Space Research* 64 (11): 2233–2244. https://doi.org/10.1016/j.asr.2019.08.042.

Chapin, F. S. 1980. "The Mineral Nutrition of Wild Plants." *Annual Review of Ecology and Systematics* 11 (1): 233–260. https://doi.org/10.1146/annurev.es.11.110180.001313.

Chatziantoniou, A., G. P. Petropoulos, and E. Psomiadis. 2017. "Co-Orbital Sentinel 1 and 2 for LULC Mapping with Emphasis on Wetlands in a Mediterranean Setting Based on Machine Learning." *Remote Sensing* 9 (12): 1259. https://doi.org/10.3390/rs9121259.

Chong, L. U. O., H. J. Liu, L. P. Lu, Z. R. Liu, F. C. Kong, and X. L. Zhang. 2021. "Monthly Composites from Sentinel-1 and Sentinel-2 Images for Regional Major Crop Mapping with Google Earth Engine." *Journal of Integrative Agriculture* 20 (7): 1944–1957. https://doi.org/10.1016/S2095-3119(20)63329-9.

Cho, M. A., and A. K. Skidmore. 2006. "A New Technique for Extracting the Red Edge Position from Hyperspectral Data: The Linear Extrapolation Method." *Remote Sensing of Environment* 101 (2): 181–193. https://doi.org/10.1016/j.rse.2005.12.011.

Clevers, J. G. P. W., S. M. De Jong, G. F. Epema, F. D. Van Der Meer, W. H. Bakker, A. K. Skidmore, and K. H. Scholte. 2002. "Derivation of the Red Edge Index Using the MERIS Standard Band Setting." *International Journal of Remote Sensing* 23 (16): 3169–3184. https://doi.org/10.1080/01431160110104647.

Croft, H., J. M. Chen, R. Wang, G. Mo, S. Luo, X. Luo, L. He, et al. 2020. "The Global Distribution of Leaf Chlorophyll Content." *Remote Sensing of Environment* 236:111479. https://doi.org/10.1016/j.rse.2019.111479.

Darvishzadeh, R., A. Skidmore, M. Schlerf, and C. Atzberger. 2008. "Inversion of a Radiative Transfer Model for Estimating Vegetation LAI and Chlorophyll in a Heterogeneous Grassland." *Remote Sensing of Environment* 112 (5): 2592–2604. https://doi.org/10.1016/j.rse.2007.12.003.

Daughtry, C. S., C. L. Walthall, M. S. Kim, E. B. De Colstoun, and J. E. McMurtrey Iii. 2000. "Estimating Corn Leaf Chlorophyll Concentration from Leaf and Canopy Reflectance." *Remote Sensing of Environment* 74 (2): 229–239. https://doi.org/10.1016/S0034-4257(00)00113-9.

Delegido, J., J. Verrelst, L. Alonso, and J. Moreno. 2011. "Evaluation of Sentinel-2 Red-Edge Bands for Empirical Estimation of Green LAI and Chlorophyll Content." *Sensors* 11 (7): 7063–7081. https://doi.org/10.3390/s110707063.

De Vroey, M., L. de Vendictis, M. Zavagli, S. Bontemps, D. Heymans, J. Radoux, B. Koetz, and P. Defourny. 2022. "Mowing Detection Using Sentinel-1 and Sentinel-2 Time Series for Large Scale Grassland Monitoring." *Remote Sensing of Environment* 280:113145. https://doi.org/10.1016/j.rse.2022.113145.

Engler, J. O., D. J. Abson, R. Feller, J. Hanspach, and H. von Wehrden. 2018. "A Social-Ecological Typology of Rangelands Based on Rainfall Variability and Farming Type." *Journal of Arid Environments* 148:65–73. https://doi.org/10.1016/j.jaridenv.2017.09.009.

Erinjery, J. J., M. Singh, and R. Kent. 2018. "Mapping and Assessment of Vegetation Types in the Tropical Rainforests of the Western Ghats Using Multispectral Sentinel-2 and SAR Sentinel-1 Satellite Imagery." *Remote Sensing of Environment* 216:345–354. https://doi.org/10.1016/j.rse.2018.07.006.

Erkovan, H. I., M. K. Gullap, M. Dasci, and K. O. C. Ali. 2009. "Changes in Leaf Area Index, Forage Quality and Above-Ground Biomass in Grazed and Ungrazed Rangelands of Eastern Anatolia Region." *Journal of Agricultural Sciences* 15 (3): 217–223. https://doi.org/10.1501/Tarimbil_0000001094.

FAO (Food and Agriculture Organization of the United Nations). 2010. *Land Degradation Assessment in Drylands (LADA): Assessing the Status Causes and Impact of Land Degradation*. Rome: FAO. https://www.fao.org/3/i6362e/i6362e.pdf.

Fernández-Habas, J., A. M. G. Moreno, M. T. Hidalgo-Fernández, J. R. Leal-Murillo, B. A. Oar, P. J. Gómez-Giráldez, M. P. González-Dugo, and P. Fernández-Rebollo. 2021. "Investigating the Potential of Sentinel-2 Configuration to Predict the Quality of Mediterranean Permanent Grasslands in Open Woodlands." *Science of the Total Environment* 791:148101. https://doi.org/10.1016/j.scitotenv.2021.148101.

Ferwerda, J. G., W. Siderius, S. E. Van Wieren, C. C. Grant, M. Peel, A. K. Skidmore, and H. H. T. Prins. 2006. "Parent Material and Fire as Principle Drivers of Foliage Quality in Woody Plants." *Forest Ecology and Management* 231 (1–3): 178–183. https://doi.org/10.1016/j.foreco.2006.05.044.

Frey, P., M. Dufresne, T. Böhm, M. Jodeau, and C. Ancey. 2006. "Experimental Study of Bed Load on Steep Slopes." In *River Flow*, 887–893. Taylor & Francis. https://lhe.epfl.ch/conf/2006RF3.

Gao, J., J. Liu, T. Liang, M. Hou, J. Ge, Q. Feng, C. Wu, and W. Li. 2020. "Mapping the Forage Nitrogen-Phosphorus Ratio Based on Sentinel-2 MSI Data and a Random Forest Algorithm in an Alpine Grassland Ecosystem of the Tibetan Plateau." *Remote Sensing* 12 (18): 2929. https://doi.org/10.3390/rs12182929.

Gelley, C., R. L. G. Nave, and G. Bates. 2016. "Forage Nutritive Value and Herbage Mass Relationship of Four Warm-Season Grasses." *Agronomy Journal* 108 (4): 1603–1613. https://doi.org/10.2134/agronj2016.01.0018.

Gitelson, A., and M. N. Merzlyak. 1994. "Quantitative Estimation of Chlorophyll-A Using Reflectance Spectra: Experiments with Autumn Chestnut and Maple Leaves." *Journal of Photochemistry and Photobiology B* 22 (3): 247–252. https://doi.org/10.1016/1011-1344(93)06963-4.

Gitelson, A. A., A. Viña, T. J. Arkebauer, D. C. Rundquist, G. Keydan, and B. Leavitt. 2003. "Remote Estimation of Leaf Area Index and Green Leaf Biomass in Maize Canopies." *Geophysical Research Letters* 30 (5). https://doi.org/10.1029/2002GL016450.

Godde, C. M., R. B. Boone, A. J. Ash, K. Waha, L. L. Sloat, P. K. Thornton, and M. Herrero. 2020. "Global Rangeland Production Systems and Livelihoods at Threat Under Climate Change and Variability." *Environmental Research Letters* 15 (4): 044021. https://doi.org/10.1088/1748-9326/ab7395.

Gorai, M., M. Ogasawara, Y. Matsuki, Y. Yamada, G. Murayama, N. Sugisaki, T. Nemoto, et al. 2014. "Weighting with the Lansbury Articular Index Improves the Correlation of Ultrasound Score with Serum Matrix Metalloproteinase-3 Level in Rheumatoid Arthritis Patients." *Modern Rheumatology* 24 (6): 915–919. https://doi.org/10.3109/14397595.2014.888794.

Grant, C. C., and M. C. Scholes. 2006. "The Importance of Nutrient Hot-Spots in the Conservation and Management of Large Wild Mammalian Herbivores in Semi-Arid Savannas." *Biological Conservation* 130 (3): 426–437. https://doi.org/10.1016/j.biocon.2006.01.004.

Gutiérrez-Jurado, H. A., and E. R. Vivoni. 2013. "Ecogeomorphic Expressions of an Aspect-Controlled Semiarid Basin: I. Topographic Analyses with High-Resolution Data Sets." *Ecohydrology* 6 (1): 8–23. https://doi.org/10.1002/eco.280.

Hastie, T., R. Tibshirani, J. H. Friedman, and J. H. Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 1–758. Vol. 2. New York: springer. https://doi.org/10.1007/978-0-387-84858-7.

Ismail, R., O. Mutanga, and L. Kumar 2010. "Modeling the Potential Distribution of Pine Forests Susceptible to Sirex Noctilio Infestations in Mpumalanga, South Africa." *Transactions in GIS* 14 (5): 709–726. https://doi.org/10.1111/j.1467-9671.2010.01229.x.

Jordan, C. F. 1969. "Derivation of Leaf-Area Index from Quality of Light on the Forest Floor." *Ecology* 50 (4): 663–666. https://doi.org/10.2307/1936256.

KavanovÁ, M., A. A. Grimoldi, F. A. Lattanzi, and H. Schnyder. 2006. "Phosphorus Nutrition and Mycorrhiza Effects on Grass Leaf Growth. P Status-And Size-Mediated Effects on Growth Zone Kinematics." *Plant, Cell & Environment* 29 (4): 511–520. https://doi.org/10.1111/j.1365-3040.2005.01428.x.

Khangura, R., D. Ferris, C. Wagg, and J. Bowyer. 2023. "Regenerative Agriculture—A Literature Review on the Practices and Mechanisms Used to Improve Soil Health." *Sustainability* 15 (3): 2338. https://doi.org/10.3390/su15032338.

Kilcast, D., ed. 2013. *Instrumental Assessment of Food Sensory Quality: A Practical Guide*. Elsevier.

Knox, N. M., A. K. Skidmore, H. H. Prins, G. P. Asner, H. M. van der Werff, W. F. de Boer, C. van der Waal, et al. 2011. "Dry Season Mapping of Savanna Forage Quality, Using the Hyperspectral Carnegie Airborne Observatory Sensor." *Remote Sensing of Environment* 115 (6): 1478–1488. https://doi.org/10.1016/j.rse.2011.02.007.

Knox, N. M., A. K. Skidmore, H. H. Prins, I. M. Heitkönig, R. Slotow, C. van der Waal, and W. F. de Boer. 2012. "Remote Sensing of Forage Nutrients: Combining Ecological and Spectral Absorption Feature Data." *ISPRS Journal of Photogrammetry and Remote Sensing* 72:27–35. https://doi.org/10.1016/j.isprsjprs.2012.05.013.

Kokaly, R. F., G. P. Asner, S. V. Ollinger, M. E. Martin, and C. A. Wessman. 2009. "Characterizing Canopy Biochemistry from Imaging Spectroscopy and Its Application to Ecosystem Studies." *Remote Sensing of Environment* 113:S78–S91. https://doi.org/10.1016/j.rse.2008.10.018.

Kokaly, R. F., and R. N. Clark. 1999. "Spectroscopic Determination of Leaf Biochemistry Using Band-Depth Analysis of Absorption Features and Stepwise Multiple Linear Regression." *Remote Sensing of Environment* 67 (3): 267–287. https://doi.org/10.1016/S0034-4257(98)00084-4.

Lacefield, G., J. C. Henning, M. Collins, and L. Swetnam. 1999. "Quality Hay Production." *Cooperative Extension Service, University Kentucky, College of Agriculture* 62 (3): 77. http://www2.ca.uky.edu/agcomm/pubs/agr/agr62/agr62.pdf.

Lymburner, L., P. J. Beggs, and C. R. Jacobson. 2000. "Estimation of Canopy-Average Surface-Specific Leaf Area Using Landsat TM Data." *Photogrammetric Engineering and Remote Sensing* 66 (2): 183–192.

Mahdianpari, M., B. Salehi, F. Mohammadimanesh, S. Homayouni, and E. Gill. 2019. "The First Wetland Inventory Map of Newfoundland at a Spatial Resolution of 10 M Using Sentinel-1 and Sentinel-2 Data on the Google Earth Engine Cloud Computing Platform." *Remote Sensing* 11 (1): 43. https://doi.org/10.3390/rs11010043.

Mahyoub, S., A. Fadil, E. M. Mansour, H. Rhinane, and F. Al-Nahmi. 2019. "Fusing of Optical and Synthetic Aperture Radar (SAR) Remote Sensing Data: A Systematic Literature Review (SLR)." *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 42:127–138. https://doi.org/10.5194/isprs-archives-XLII-4-W12-127-2019.

Manolikaki, I., N. Digalaki, G. Psarras, C. Tzerakis, C. Sergentani, A. Papamanolioudaki, S. Tul, and G. Koubouris. 2022. "Seasonal Variation of Leaf Ca, Fe, and Mn Concentration in Six Olive Varieties." *International Journal of Plant Biology* 13 (2): 95–105. https://doi.org/10.3390/ijpb13020010.

Marsett, R. C., J. Qi, P. Heilman, S. H. Biedenbender, M. C. Watson, S. Amer, M. Weltz, D. Goodrich, and R. Marsett. 2006. "Remote Sensing for Grassland Management in the Arid Southwest." *Rangeland Ecology & Management* 59 (5): 530–540. https://doi.org/10.2111/05-201R.1.

McDermot, C., and S. Elavarthi. 2014. "Rangelands As Carbon Sinks to Mitigate Climate Change: A Review." *Journal of Earth Science and Climate Change* 5 (08): 221. https://doi.org/10.4172/2157-7617.1000221.

Meneghini, A. 2019. "An Evaluation of Sentinel-1 and Sentinel-2 for Land Cover Classification." International Development, Community and Environment (IDCE), 235. https://commons.clarku.edu/idce_masters_papers/23.

Moore, K. J., and H. J. G. Jung. 2001. "Lignin and Fiber Digestion." *Journal of Range Management* 54 (4). http://dx.doi.org/10.2307/4003113.

Mundalamo, T. D. 2019. *Characterizing Historic Land Use and Land Cover Change Using Landsat Earth Observation Data in the Waterberg Biosphere Reserve*. Johannesburg: Faculty of Science, University of the Witwatersrand. https://hdl.handle.net/10539/28062.

Mutanga, O., A. K. Skidmore, and H. H. T. Prins. 2004. "Predicting in situ Pasture Quality in the Kruger National Park, South Africa, Using Continuum-Removed Absorption Features." *Remote Sensing of Environment* 89 (3): 393–408. https://doi.org/10.1016/j.rse.2003.11.001.

Nazarova, T., P. Martin, and G. Giuliani. 2020. "Monitoring Vegetation Change in the Presence of High Cloud Cover with Sentinel-2 in a Lowland Tropical Forest Region in Brazil." *Remote Sensing* 12 (11): 1829. https://doi.org/10.3390/rs12111829.

Nesamvuni, E., S. A. Oni, J. J. Odhiambo, and N. D. Nthakheni. 2003. *Agriculture a Corner Stone of the Economy of the Limpopo Province*. Limpopo Department of Agriculture, Polokwane. https://www.worldcat.org/title/agriculture-as-the-cornerstone-of-the-economy-of-the-limpopo-province/oclc/56424792.

Nie, Z., and M. R. Norton. 2009. "Stress Tolerance and Persistence of Perennial Grasses: The Role of the Summer Dormancy Trait in Temperate Australia." *Crop Science* 49 (6): 2405–2411. https://doi.org/10.2135/cropsci2009.06.0320.

Onojeghuo, A. O., A. R. Onojeghuo, M. Cotton, J. Potter, and B. Jones. 2021. "Wetland Mapping with Multi-Temporal Sentinel-1 &-2 Imagery (2017–2020) and LiDAR Data in the Grassland Natural Region of Alberta." *GIScience & Remote Sensing* 58 (7): 999–1021. https://doi.org/10.1080/15481603.2021.1952541.

Palmer, T., and A. Ainslie. 2006. "Country Pasture/Forage Resource Profiles." *Food and Agriculture Organization*. https://ees.kuleuven.be/eng/klimos/toolkit/documents/658SouthAfricaEnglish.pdf .

Parida, B. R., and A. Kumari. 2021. "Mapping and Modeling Mangrove Biophysical and Biochemical Parameters Using Sentinel-2A Satellite Data in Bhitarkanika National Park, Odisha." *Modeling Earth Systems and Environment* 7:2463–2474. https://doi.org/10.1007/s40808-020-01005-3.

Pontes, L. D. S., P. Carrere, D. Andueza, F. Louault, and J. F. Soussana. 2007. "Seasonal Productivity and Nutritive Value of Temperate Grasses Found in Semi-Natural Pastures in Europe: Responses to Cutting Frequency and N Supply." *Grass and Forage Science* 62 (4): 485–496. https://doi.org/10.1111/j.1365-2494.2007.00604.x.

Potts, L. J., J. D. Gantz, Y. Kawarasaki, B. N. Philip, D. J. Gonthier, A. D. Law, L. Moe, et al. 2020. "Environmental Factors Influencing Fine-Scale Distribution of Antarctica's Only Endemic Insect." *Oecologia* 194 (4): 529–539. https://doi.org/10.1007/s00442-020-04714-9.

Qi, J., A. Chehbouni, A. R. Huete, Y. H. Kerr, and S. Sorooshian. 1994. "A Modified Soil Adjusted Vegetation Index." *Remote Sensing of Environment* 48 (2): 119–126. https://doi.org/10.1016/0034-4257(94)90134-1.

Raab, C., F. Riesch, B. Tonn, B. Barrett, M. Meißner, N. Balkenhol, and J. Isselstein. 2020. "Target-Oriented Habitat and Wildlife Management: Estimating Forage Quantity and Quality of Semi-Natural Grasslands with Sentinel-1 and Sentinel-2 Data." *Remote Sensing in Ecology and Conservation* 6 (3): 381–398. https://doi.org/10.1002/rse2.149.

Ramachandra Rao, S., and G. A. Ravishankar. 2002. "Plant Cell Cultures: Chemical Factories of Secondary Metabolites." *Biotechnology Advances* 20:101–153. https://doi.org/10.1016/S0734-9750(02)00007-1.

Ramoelo, A., and M. A. Cho. 2018. "Explaining Leaf Nitrogen Distribution in a Semi-Arid Environment Predicted on Sentinel-2 Imagery Using a Field Spectroscopy Derived Model." *Remote Sensing* 10 (2): 269. https://doi.org/10.3390/rs10020269.

Ramoelo, A., M. A. Cho, R. Mathieu, S. Madonsela, R. Van De Kerchove, Z. Kaszta, and E. Wolff. 2015. "Monitoring Grass Nutrients and Biomass as Indicators of Rangeland Quality and Quantity Using Random Forest Modelling and WorldView-2 Data." *International Journal of Applied Earth Observation and Geoinformation* 43:43–54. https://doi.org/10.1016/j.jag.2014.12.010.

Ramoelo, A., M. A. Cho, R. S. Mathieu, A. K. Skidmore, M. Schlerf, and I. M. A. Heitkönig. 2012. "Estimating Grass Nutrients and Biomass As an Indicator of Rangeland (Forage) Quality and Quantity Using Remote Sensing in Savanna Ecosystems." 9th International Conference of the African Association of Remote Sensing and the Environment (AARSE). http://hdl.handle.net/10204/6478.

Ramoelo, A., N. Majozi, R. Mathieu, N. Jovanovic, A. Nickless, and S. Dzikiti. 2014. "Validation of Global Evapotranspiration Product (MOD16) Using Flux Tower Data in the African Savanna, South Africa." *Remote Sensing* 6 (8): 7406–7423. https://doi.org/10.3390/rs6087406.

Ramoelo, A., A. K. Skidmore, M. A. Cho, R. Mathieu, I. M. A. Heitkönig, N. Dudeni-Tlhone, M. Schlerf, and H. H. T. Prins. 2013. "Non-Linear Partial Least Square Regression Increases the Estimation Accuracy of Grass Nitrogen and Phosphorus Using in situ Hyperspectral and Environmental Data." *ISPRS Journal of Photogrammetry and Remote Sensing* 82:27–40. https://doi.org/10.1016/j.isprsjprs.2013.04.012.

Ramoelo, A., C. Stolter, D. Joubert, M. A. Cho, A. Groengroeft, O. R. Madibela, I. Zimmermann, and H. Pringle. 2018. "Rangeland Monitoring and Assessment: A Review." *Biodiversity & Ecology* 6:170–176. https://doi.org/10.7809/b-e.00320.

Richardson, A. J., and C. L. Wiegand. 1977. "Distinguishing Vegetation from Soil Background Information." *Photogrammetric Engineering and Remote Sensing* 43 (12): 1541–1552.

Rouse, J. W., R. H. Haas, J. A. Schell, and D. W. Deering. 1974. "Monitoring Vegetation Systems in the Great Plains with ERTS." *NASA Special Publication* 351 (1): 309.

Rutkowski, J., M. J. Canty, and A. A. Nielsen. 2018. "Site Monitoring with Sentinel-1 Dual Polarization SAR Imagery Using Google Earth Engine." *Journal of Nuclear Materials Management* 46 (3): 48–59.

Salido, E. M., L. N. Servalli, J. C. Gomez, and C. Verrastro. 2017. "Phototransduction Early Steps Model Based on Beer-Lambert Optical Law." *Vision Research* 131:75–81. https://doi.org/10.1016/j.visres.2016.12.012.

Schachtman, D. P., R. J. Reid, and S. M. Ayling. 1998. "Phosphorus Uptake by Plants: From Soil to Cell." *Plant Physiology* 116 (2): 447–453. https://doi.org/10.1104/pp.116.2.447.

Schmidt, K. S., and A. K. Skidmore. 2001. "Exploring Spectral Discrimination of Grass Species in African Rangelands." *International Journal of Remote Sensing* 22 (17): 3421–3434. https://doi.org/10.1080/01431160152609245.

Shang, Y., G. Liu, Z. Wen, P. A. Jacinthe, K. Song, B. Zhang, L. Lyu, S. Li, X. Wang, and X. Yu. 2021. "Remote Estimates of CDOM Using Sentinel-2 Remote Sensing Data in Reservoirs with Different Trophic States Across China." *Journal of Environmental Management* 286:112275. https://doi.org/10.1016/j.jenvman.2021.112275.

Sims, D. A., and J. A. Gamon. 2002. "Relationships Between Leaf Pigment Content and Spectral Reflectance Across a Wide Range of Species, Leaf Structures and Developmental Stages." *Remote Sensing of Environment* 81 (2–3): 337–354. https://doi.org/10.1016/S0034-4257(02)00010-X.

Spangler, L., G. F. Vance, G. E. Schuman, and J. D. Derner. 2012. *Rangeland Sequestration Potential Assessment*. Montana State Univ. Bozeman: MT (United States). https://doi.org/10.2172/1037875 .

Thapa, S. K., J. F. de Jong, A. R. Hof, N. Subedi, L. R. Joshi, and H. H. Prins. 2022. "Fire and Forage Quality: Postfire Regrowth Quality and Pyric Herbivory in Subtropical Grasslands of Nepal." *Ecology and Evolution* 12 (4): e8794. https://doi.org/10.1002/ece3.8794.

Thornton, P. K. 2010. "Livestock Production: Recent Trends, Future Prospects. *Philosophical Transactions of the Royal Society of London*." *Series B, Biological Sciences* 365 (1554): 2853–2867. https://doi.org/10.1098/rstb.2010.0134.

Tian, D., and S. Niu. 2015. "A Global Analysis of Soil Acidification Caused by Nitrogen Addition." *Environmental Research Letters* 10 (2): 024019. https://doi.org/10.1088/1748-9326/10/2/024019.

Trivedi, M. B. 2020. *Mapping Probabilities of Arable Fields Using Modis, Sentinel-1 and Sentinel-2 Based Image Features in Ghana* Master's thesis, University of Twente. https://purl.utwente.nl/essays/85199 .

Trollope, W. S. W. 2011. "Personal Perspectives on Commercial versus Communal African Fire Paradigms When Using Fire to Manage Rangelands for Domestic Livestock and Wildlife in Southern and East African Ecosystems." *Fire Ecology* 7 (1): 57–73. https://doi.org/10.4996/fireecology.0701057.

Ustin, S. L., and S. Jacquemoud. 2020. "How the Optical Properties of Leaves Modify the Absorption and Scattering of Energy and Enhance Leaf Functionality." *Remote Sensing of Plant Biodiversity*: 349–384. https://doi.org/10.1007/978-3-030-33157-3.

Van Soest, P. V., J. B. Robertson, and B. A. Lewis. 1991. "Methods for Dietary Fiber, Neutral Detergent Fiber, and Nonstarch Polysaccharides in Relation to Animal Nutrition." *Journal of Dairy Science* 74 (10): 3583–3597. https://doi.org/10.3168/jds.S0022-0302(91)78551-2.

Veloso, A., S. Mermoz, A. Bouvet, T. Le Toan, M. Planells, J. F. Dejoux, and E. Ceschia. 2017. "Understanding the Temporal Behavior of Crops Using Sentinel-1 and Sentinel-2-Like Data for Agricultural Applications." *Remote Sensing of Environment* 199:415–426. https://doi.org/10.1016/j.rse.2017.07.015.

Venables, W. N., D. M. Smith, and R. Core Team. 2015. "An Introduction to R: A Programming Environment for Data Analysis and Graphics Version 3.1. 2."

Venter, Z. S., H. J. Hawkins, and M. D. Cramer. 2017. "Implications of Historical Interactions Between Herbivory and Fire for Rangeland Management in African Savannas." *Ecosphere* 8 (10): e01946. https://doi.org/10.1002/ecs2.1946.

Vera-Velez, R., S. A. Grover, B. K. Bischoff, C. N. Carlyle, and E. G. Lamb. 2023. "Wildfire-Grazing Impact on Forage Quality Assessed with Near-Infrared Spectroscopy and Generalized Partial Least Squares Regression." *Rangeland Ecology & Management* 87:132–140. https://doi.org/10.1016/j.rama.2023.01.003.

Verrelst, J., J. Muñoz, L. Alonso, J. Delegido, J. P. Rivera, G. Camps-Valls, and J. Moreno. 2012. "Machine Learning Regression Algorithms for Biophysical Parameter Retrieval: Opportunities for Sentinel-2 And-3." *Remote Sensing of Environment* 118:127–139. https://doi.org/10.1016/j.rse.2011.11.002.

Wachendorf, M., T. Fricke, and T. Möckel. 2018. "Remote Sensing as a Tool to Assess Botanical Composition, Structure, Quantity and Quality of Temperate Grasslands." *Grass and Forage Science* 73 (1): 1–14. https://doi.org/10.1111/gfs.12312.

Wang, R., and J. A. Gamon. 2019. "Remote Sensing of Terrestrial Plant Biodiversity." *Remote Sensing of Environment* 231:111218. https://doi.org/10.1016/j.rse.2019.111218.

Wang, L., S. Sun, T. Wu, L. Liu, X. Sun, Y. Cai, J. Li, et al. 2020. "Natural Variation and Crispr/cas9-Mediated Mutation in GmPrr37 Affect Photoperiodic Flowering and Contribute to Regional Adaptation of Soybean." *Plant Biotechnology Journal* 18 (9): 1869–1881. https://doi.org/10.1111/pbi.13346.

Wang, F., R. Wang, and Z. He. 2021. "The Impact of Environmental Pollution and Green Finance on the High-Quality Development of Energy Based on Spatial Dubin Model." *Resources Policy* 74:102451. https://doi.org/10.1016/j.resourpol.2021.102451.

Wang, J., X. Xiao, R. Bajgain, P. Starks, J. Steiner, R. B. Doughty, and Q. Chang. 2019. "Estimating Leaf Area Index and Aboveground Biomass of Grazing Pastures Using Sentinel-1, Sentinel-2 and

Landsat Images." *ISPRS Journal of Photogrammetry and Remote Sensing* 154:189–201. https://doi.org/10.1016/j.isprsjprs.2019.06.007.

Weltz, M. A., G. Dunn, J. Reeder, and G. Frasier. 2003. "Ecological Sustainability of Rangelands." *Arid Land Research and Management* 17 (4): 369–388. https://doi.org/10.1080/713936117.

Zhang, W., M. Brandt, Q. Wang, A. V. Prishchepov, C. J. Tucker, Y. Li, H. Lyu, and R. Fensholt. 2019. "From Woody Cover to Woody Canopies: How Sentinel-1 and Sentinel-2 Data Advance the Mapping of Woody Plants in Savannas." *Remote Sensing of Environment* 234:111465. https://doi.org/10.1016/j.rse.2019.111465.