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Characterizing the spatio-temporal variations of C3 and C4 dominated grasslands aboveground biomass in the Drakensberg, South Africa

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Abstract

C3 and C4 grass species composition, with different physiological, morphological and most importantly phenological characteristics, influence Aboveground Biomass (AGB) and their ability to provide ecosystem goods and services, over space and time. For decades, the lack of appropriate remote sensing data sources compromised C3 and C4 grasses AGB estimation, over space and time. This resulted in uncertainties in understanding their potential and contribution to the provision of services. This study therefore examined the utility of the new multi-temporal Sentinel 2 to estimate and map C3 and C4 grasses AGB over time, using the advanced Sparse Partial Least Squares Regression (SPLSR) model. Overall results have shown the variability in AGB between C3 and C4 grasses, estimation accuracies and the performance of the SPLSR model, over time. *Themeda* (C4) produced higher AGB from February to April, whereas from May to September, *Festuca* produced higher AGB. Both species also showed a decrease in AGB in August and September, although this was most apparent for *Themeda* than its counterpart. Spectral bands information predicted species AGB with lowest accuracies and an improvement was observed when both spectral bands and vegetation indices were applied. For instance, in the month of May, spectral bands predicted species AGB with lowest accuracies for *Festuca* (R^2 = 0.57; 31.70% of the mean), *Themeda* (R^2 = 0.59; 24.02% of the mean) and combined species (R^2 = 0.61; 15.64% of the mean); the use of spectral bands and vegetation indices yielded 0.77; (18.64%), 0.75 (14.27%) and 0.73 (16.47%), for *Festuca, Themeda* and combined species, respectively. The red edge (at 0.705 and 0.74 µm) and derived indices, NIR and SWIR 2 (2.19 µm) were found to contribute more to grass species AGB estimation, over time. Findings have also revealed the potential of the SPLSR model in estimating C3 and C4 grasses AGB using Sentinel 2 images, over time. The AGB spatial variability maps produced in this study can be used to quantify C3 and C4 forage availability or accumulating fuel, as well as for developing operational management strategies.

1. Introduction

C3 and C4 grass species Aboveground Biomass (AGB) represent a fundamental indicator of their productivity, which directly influences the ability of these ecosystems to provide ecosystem goods and services. Grass species productivity provides a wide range of ecological, economic and environmental services. For instance, these grasses are an important source of forage for livestock and wildlife populations (Diouf et al., 2015; Mansour et al., 2013), as well as a source of fuel load for fire occurrences, which is an important mechanism in their maintenance (Everson and Everson, 2016). Within the global carbon cycle, C4 grasses also store a substantial amount of carbon, compared to C3 grasses (Adair and Burke, 2010). Besides, the Intergovernmental Panel on Climate Change (IPCC) identified species AGB as one of the principal carbon pools of terrestrial ecosystems (Eggleston et al., 2006; Kumar and Mutanga, 2017; Vashum and Jayakumar, 2012). Most importantly, the phenological differences between C3 and C4 grass species, as determined by seasonal variations in climatic conditions influence their AGB over time. However, although a lot of studies have reported the phenological differences between C3 and C4, from a local scale, they tend to be more variable, due to the influence of local environmental conditions, such as topography. Consequently, the potential of these grasses to provide services is different and this may be more variable over space and time.

The current and projected environmental changes also threaten the spatial and temporal productivity of C3 and C4 grass species, with implications on AGB timing, accumulation and variations (Adjorlolo et al., 2012; Bremond et al., 2012; Joubert et al., 2017; Morris, 2017). Compelling evidence have also reported substantial response of C3 and C4 grasses AGB to carbon dioxide (CO_2) fluctuations (Lee, 2011; Polley et al., 2014; White et al., 2012), water availability (Niu et al., 2008) and temperature changes (Auerswald et al., 2012; Still et al., 2014). Considerable uncertainties about the response of C3 and C4 grass species also exist under a CO_2-enriched, warmer environment and the influence of local conditions (Chamaillé-Jammes and Bond, 2010). Nevertheless, environmental changes compromise the integrity of C3 and C4 grasses functional types and subsequently the provision of a range of services, such as forage and carbon storage. In this regard, the estimation of C3 and C4 grass species AGB over time provides detailed understanding of their productivity and response to environmental variability over time. This becomes a fundamental step to identify areas of low or high productivity, for example, in the case of forage availability, or determines vulnerable areas to environmental changes. This is required for developing proper management strategies to ensure sustainable provision of ecosystem goods and services.

Remote sensing remains a realistic and practical data source, for spatially explicit characterization of C3 and C4 grasses AGB over time and space. So far, AGB estimation for C3 and C4 grasses has been conducted or reported on specific seasonal period, using broadband multi-spectral datasets (Grant et al., 2013; Lu et al., 2009; Pau and Still, 2014). In a different study, Shoko et al. (2016) conducted a detailed review on the progress of C3 and C4 grass species AGB estimation using remote sensing. The review found that the majority of studies which estimated C3 and C4 AGB were done using Moderate Resolution Imaging Spectroradiometer (MODIS), the Advanced Very High Resolution Radiometer (AVHRR), MEdium Resolution Imaging Spectrometer (MERIS) and Landsat multi-spectral datasets in the Prairies or Great Plains of the United States and in the temperate region of China. The challenges associated with using these datasets were also noted, which included lower estimation accuracies and spatial representation of AGB. This has been primarily attributed to mixed-pixel problem, due to their coarse spatial resolutions. These datasets also constitute limited number and strategically-positioned bands (*e.g.* red edge), which limit their spectral potential in differentiating C3 and C4 species characteristics associated with AGB variations. Their coarse spatial resolution (*e.g.* 1 km for MODIS and AVHRR) also misrepresent AGB spatial variations. With these challenges, other researchers (e.g. Lu et al., 2009) attempted to use hyperspectral datasets, with high spatial resolution and narrow spectral bands. These datasets have been reported to yield high predictive accuracies, compared to multispectral. However, their application did not receive enough attention from the research community, especially for AGB estimation at large geographical coverage over time. This has been due to their high acquisition cost; hence their application has been limited to small geographical coverage, especially in resource-constrained regions like Africa. The use of hyperspectral data sources becomes insufficient for the development of appropriate management strategies, especially considering the influence of climatic variations on C3 and C4 AGB over time. In this regard, AGB spatial and temporal variations for C3 and C4 grasses remains poorly documented. However, future prospects in understanding the productivity between C3 and C4 depend on the use of new generation freely-available sensors, such as the Sentinel 2.

Currently, the readily-available Sentinel 2 is perceived to provide a major key data source for estimating C3 and C4 grasses AGB over time, in a cost effective manner, at large geographical coverage. Although Sentinel 2 earth imaging characteristics are not as advanced as hyper-spectral data (*e.g.* in terms of spatial resolution), the sensor might be considered as an intermediate dataset between the freely-available broadband multispectral sensors and more advanced and commercialized hyperspectral sensors. The characteristics of Sentinel 2 overcome the major challenges associated with the operational application of broadband and medium resolution satellites, such as MODIS, AVHRR, MERIS and Landsat data series, which have been the primary data sources for AGB estimation, across C3 and C4 grasslands. The sensor is equipped with state-of-the-art instrumentation, which offers high resolution optical images, when compared to freely-available satellites on board optical or multispectral sensors, such as Landsat 8 or ETM 7 (Addabbo et al., 2016). Increased and unique spectral bands (13) at different and refined portions of the electromagnetic spectrum of Sentinel 2 free of charge provide more spectral windows sensitive to species morphological, physiological and phenological characteristics, which influence the production of AGB. This may improve the estimation accuracy of C3 and C4 grass species over space and time. In addition, these bands are only available in commercial datasets, such as hyperspectral, hence Sentinel 2 provide free access to the unique bands. The high revisit frequency (5-19 days), most importantly, captures the phenological variations of C3 and C4 grass, which influence AGB variations over time, as well as enabling the acquisition of cloud-free images. The 290 km swath-width also allows large geographic coverage, which is one of the major limitations of using hyperspectral data, whereas the 10 m spatial resolution captures AGB spatial variations at a finer scale, appropriate for mapping, especially considering the co-existence of C3 and C4 grass species, with varying characteristics.

Sentinel 2 sensor has so far proved a great potential in estimating and mapping crop quality (Clevers et al., 2017; Immitzer et al., 2016), vegetation health (Addabbo et al., 2016), wood cover mapping (Munyati, 2017), as well as C3 and C4 grass species discrimination and mapping (Shoko and Mutanga, 2017a). However, its applicability in C3 and C4 grass AGB estimation over time is still rudimentary despite the immediate need of information on rangeland productivity, in the face of the changing climate. This study therefore used time-series Sentinel 2 data to estimate and map C3 and C4 dominated grasslands AGB, in the Drakensberg, KwaZulu-Natal, over time. The study also aimed at determining the consistency of Sentinel 2 derivatives in estimating species AGB, over space and time.

2. Materials and methods

2.1. Study area

The AGB estimation for C3 and C4 grass species was conducted within the Drakensberg area in the province of KwaZulu-Natal (presented in Fig. 1), which is one of the key grassland areas in South Africa (Everson and Everson, 2016). The climate of the area is predominantly wet humid summers and dry, cold winters. The summer period begins in November and ends in March (Nel, 2009), with high total rainfall received between 990 and 1130 mm, whereas the winter period begins in May until August, associated with regular frosts and snowfall (Dollar and Goudy, 1999; Mansour et al., 2012). Temperatures also vary, with a minimum of 5 °C in winter and a maximum of 16 °C in summer (Everson and Everson, 2016). In addition, this area has been regarded as a transitional zone, which is vulnerable to environmental changes, posing a significant threat to its productivity. The elevation of the study area is also quiet variable, ranging between 1 225 and 3 034 m (Shoko and Mutanga, 2017b). The distributional map of the target C3 and C4 grass species was derived, using Sentinel 2 optimal variables, during an optimal period. A separate study was done to determine the optimal period for the discrimination and mapping of these species, using Sentinel 2 multi-temporal images in 2016. It was found that images acquired in winter, particularly in May and June have better classification accuracies, compared to those acquired in summer. In this regard, the map used for this study was derived, using an image acquired in June, which was found to have the highest overall classification accuracy (93.5%) associated with lowest misclassification errors (between 2 and 10%) for the two species.

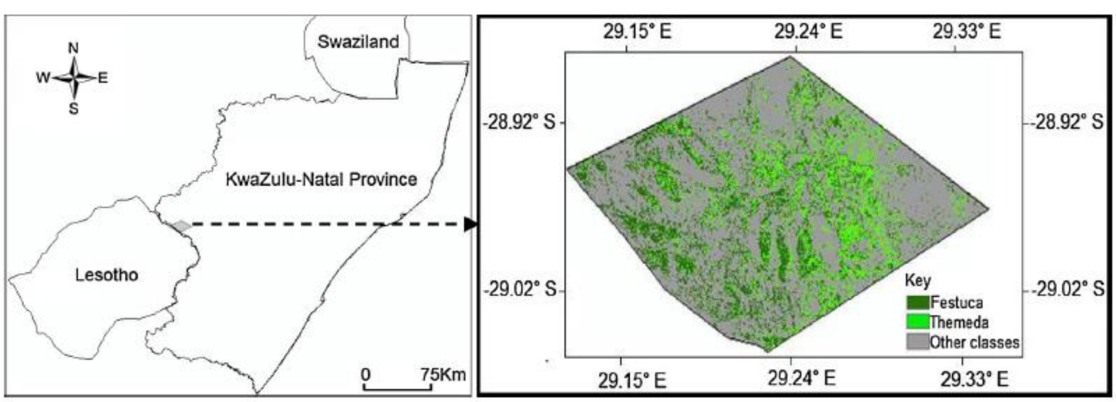

Fig. 1. The location of the study area, indicating the distribution of target grasses in the Drakensberg area, using Sentinel 2 satellite data, acquired in June 2016.

Fig. 2. A field view of *Festuca* (left) and *Themeda* (right) grass species, (May 2016).

2.2. Data collection

The target grass species; *Festuca,* C3 and *Themeda,* C4 are illustrated in Fig. 2. The collection of AGB for these species was conducted in early February, May, August and November 2016, using randomly generated points. At each point, three quadrats, measuring 50 cm by 50 cm were used to collect grasses AGB samples within a 10 by 10 m plot. In each quadrant, standing grass AGB was harvested and its weight was determined *in situ*. The grass AGB samples were then transported and oven dried at the University of KwaZulu-Natal grassland facilities, to determine dry AGB. The dry AGB was weighed and this was converted to kilograms per square metre (kg/m^2). A total of 80 plots, measured 10 by 10 m were used for each species, with 3 samples per plot. This resulted in a total of 240 AGB samples for each species, which were used for analysis during each acquisition period. AGB sample locations were also captured and recorded using a handheld global position system (GPS), with sub-meter accuracy.

2.3. Remote sensing data acquisition and processing

Sentinel 2A images are freely-available for download from the European Space Agency (ESA) website (https://scihub.copernicus.eu/), through the Sentinels Scientific Data Hub archive. Eight cloud-free Sentinel 2 MSI Level 1C images (Table 1), covering the entire study area were selected and downloaded for AGB estimation over time. Sentinel 2 sensor acquires images using 13 spectral bands, four bands at 10 m spatial resolution, featuring blue (0.49 µm), green (0.56 µm), red (0.665 µm) and near-infrared (0.842 µm), six bands at 20m, with four narrow bands in the vegetation red-edge spectral domain (0.705, 0.74, 0.783 and 0.865 µm) and two SWIR, at 1.61 and 2.19 µm. Sentinel 2 spectral range also offers cirrus (0.443 µm), water vapour (0.945 µm) and aerosol (1.38 µm) bands, at 60 m spatial resolution, which have been dedicated to atmospheric monitoring. For this study, ten bands were therefore used, with the exception of cirrus, water vapour and aerosol bands, and all bands at 20 m were resampled to 10 m spatial resolution using nearest neighbour resampling in Sentinels Application Platform (SNAP) environment. Sentinel 2 images are delivered orthorectified and geometrically corrected top of atmosphere reflectance in Universal Transverse Mercator projection and World Geodetic System (WGS) 84 ellipsoid. The images were therefore corrected for atmospheric effects using the Sen2Cor prototype processing tool in SNAP.

2.4. Regression algorithm for predicting Festuca and Themeda grass species AGB

This study used the Sparse Partial Least Square Regression (SPLSR) to predict AGB variations between *Festuca*, C3 and *Themeda*, C4 grass species. SPLSR is one of the robust and powerful non-parametric model with reported potential in predicting vegetation biophysical properties using remote sensing data (Verrelst et al., 2012).

Table 1
Sentinel 2 image acquisition characteristics.

Season	Acquisition period	Sun zenith angle (°)	Sun azimuth angle (°)
Summer	**07/02/2016**	41.57	44.02
	05/03/2016	46.94	36.32
	03/11/2016	24.59	60.95
	03/12/2016	22.41	77.97
Winter	**14/05/2016**	55.99	28.94
	26/06/2016	58.34	29.29
	25/08/2016	47.16	37.10
	29/09/2016	36.49	43.65

*Bolded acquisition periods are those months in which ground measurements of species AGB were collected, whereas those in regular format were the images that were used to predict using models developed from ground-based measurements.

It is the more advanced version of the normal PLSR and the study by Abdel-Rahman et al. (2014) revealed detailed differences between them. Compared to its predecessor, the SPLSR performs dimensionality reduction and variable selection simultaneously and when it transforms the data, the SPLSR enforces sparsity and picks out the most suitable remote sensing variables for estimation. This enabled the recent studies in grass AGB estimation to shift towards its adoption. For example, SPLSR has been reported to perform well in predicting AGB for grasses under different management practices (Sibanda et al., 2017; Sibanda et al., 2015b), with reliable accuracy, using different remote sensing datasets, including hyperspectral and multispectral imagery. SPLSR predicts AGB using the remote sensing variables and ground-based measurements. The model also provides the most optimal variables for predicting AGB, using the variable importance projection (VIP) scores, which are allocated to each variable. Variables with values above the VIP threshold of the SPLSR (*i.e.* VIP > 1) are regarded as significantly important, whereas those below the threshold are less important in estimating AGB. The VIP scores were therefore used to determine the frequency of each variable. Frequency in this regard was the number of occurrences of each important variable, when its value was above the threshold, in estimating species AGB over the period of study. The model was run 4 times, using ground measured AGB values collected in February, May, August and November with three sets of variables. This resulted in a total of 12 runs and variable frequency was reported when using (i) spectral bands only, (ii) vegetation indices only and (iii) spectral bands +

vegetation indices. Before the model was run, the field-based AGB data samples were randomly split into 70%, which was used to train the model, whereas the remaining 30% was used for validation. Consequently, for each species 56 plots (*i.e.* 168 samples) were used for training, whereas 24 (*i.e.* 72 samples) were used for validation. This also resulted in 336 samples for training and 144 samples for validation, for species pooled dataset.

2.5. Sentinel 2 variables used to predict grass species AGB

Three sets of variables from the Sentinel 2 images were used to predict AGB using the SPLSR and these include: (i) image data (ii) derived vegetation indices (VIs) and (iii) a combination of indices and image data. All the Sentinel 2 derived variables that were used to predict AGB are provided in Table 2. VIs were chosen based on their performance in C3 and C4 grass species compositions AGB (Rigge et al., 2013; Tieszen et al., 1997). The indices chosen have been frequently used since the potential of remote sensing in C3 and C4 AGB estimation has been recognized and had shown great potential using different datasets. In addition, red edge-based simple ratio (SR) and normalized difference vegetation index (NDVI), which were previously reported (Ramoelo et al., 2015) to perform well across grasslands ecosystems in general were adopted to predict AGB variations for C3 and C4 grass species. Red-edge based indices have not yet been fully utilised in estimating C3 and C4 grass species AGB. Previously-used sensors for estimating C3 and C4 grasses AGB does not constitute red edge bands, the majority of studies have used red and NIR-based NDVI and SR. The inclusion of red edge-based indices in this study therefore provides more insight on the performance of these indices derived using different spectral bands and enlightens prospects for future AGB monitoring of these grasses. The indices were named based on the red edge band used, for example, NDVIRE1 and SRRE1 were derived using red edge band 1. A total of 24 variables were used in this analysis, with 12 analysis using each variable set (*i.e.* spectral bands, indices and bands + indices), for the whole study period.

2.6 Species AGB accuracy assessment

Statistical measures of the estimation accuracy over time, using the different variables were determined. These measures were the coefficient of determination (R^2) and root mean square error (RMSE) and% RMSE. The RMSE is a measure of the difference between the actual measured AGB values in the field and the estimated values by the model, whereas%RMSE is its deviation from the measured values expressed as a percentage. By expressing the RMSE as a% (within a scale between 0 and 100%) more insight is provided on the magnitude of deviation of AGB estimates using the different Sentinel 2 variables. These accuracy measures are frequently used in prediction accuracy assessment, using remote sensing data, for example by Dube and Mutanga (2015) and Adam et al. (2014). From each analysis using the field-based measurement, a better model was identified, and the selected model and associated variables was then used to produce AGB map for the study area.

2.7 *Species AGB spatial predictions over time*

Four AGB models were developed (two for summer and two for winter), which correspond with the field measured data. These models were used to produce AGB maps for the study area during the field data acquisition period, as well as for the subsequent months in which AGB measurements were not available. For instance, the model developed and associated VIP variable, using AGB measurements collected in February 2016 was used to estimate AGB variations for March 2016. In addition, the predicted AGB maps were also used to extract species AGB, using the GPS points. The extracted AGB values were then used to derive descriptive statistics of the target grass species, over time.

3. Results

3.1. Measured species AGB over time

Fig. 3 shows summary statistics, which include the maximum, minimum and average of the measured dry AGB for the two species, in kg/m^2, over time. The measured AGB shows temporal variations between the two grasses. For *Festuca* grass, the highest AGB was recorded in May, whereas for *Themeda,* the highest AGB was measured in November.

Table 2
Sentinel 2 variables that were used to predict species AGB over time.

Data type	Details	Analysis set
Original image data	Ten spectral bands Bands 2–8A (Blue, Green, Red, Red edge1-3, NIR, Red edge4) Bands 11 and 12 (Shortwave infrared bands)	i
Derived Vegetation Indices (VIs)	EVI, SAVI, NDVI, RDVI, SR, MSR, red edge-based NDVI (using red edge bands 1–4), red edge-based SR (using red edge bands 1–4),	ii
Image spectral data + VIs	Combined image spectral bands and vegetation indices	iii

EVI: Enhanced vegetation index (Huete et al., 1997), SAVI: Soil adjusted vegetation index (Huete, 1988), NDVI: normalized difference vegetation index (Tucker, 1979), RDVI: re-normalized difference vegetation index (Roujean and Breon, 1995), SR: simple ratio (Jordan, 1969).

4. Performance of Sentinel 2 derived variables in predicting grasses AGB over time

Table 3 provides the statistical measures of accuracies for estimating *Festuca*, *Themeda* and combined species dataset AGB, using spectral bands, indices and spectral bands plus indices in February, May, August and November 2016. These results are from the 70% dataset. Overall, Sentinel 2 derived variables yielded higher accuracies, which are quite variable over time. Spectral bands predicted species AGB with lower accuracies and this increase when indices and a combination of spectral bands were used.

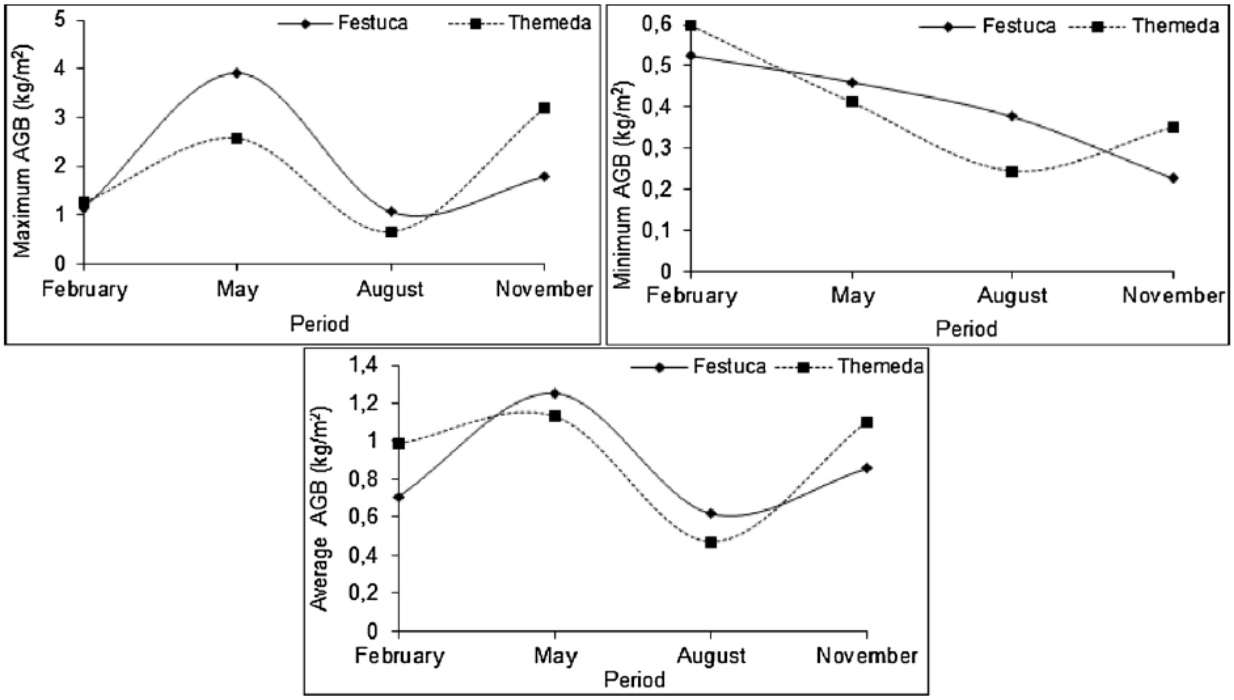

Fig. 3. Maximum, minimum and average species AGB, based on field dataset, over time.

For instance, in May, spectral bands predicted species AGB with lower accuracies for *Festuca* (R^2 = 0.57; 31.70% of the mean), *Themeda* (R^2 = 0.59; 24.02% of the mean) and combined species (R^2 = 0.61; 15.64% of the mean). Indices improved the prediction accuracies for *Festuca* (R^2 = 0.70; 22.05% of the mean), *Themeda* (R^2 = 0.69; 16.51% of the mean) and combined species (R^2 = 0.70; 23.15% of the mean). Comparably, spectral bands + indices yielded the highest accuracies for *Festuca* (R^2 = 0.77; 18.64% of the mean), *Themeda* (R^2 = 0.75; 14.27% of the mean) and combined species (R^2 = 0.73; 16.47% of the mean). Similar pattern in the improvement of prediction accuracies from using spectral bands to the combination of bands and indices was found in February, August and November.

Results also clearly show that the performance of predictive variables varied with seasonal period. For instance, lowest prediction accuracies were found in May using spectral bands for *Festuca* (R^2 = 0.57; 31.70% of the mean), *Themeda* (R^2 = 0.59; 24.08% of the mean) and combined species (R^2 = 0.57; 28.11% of the mean). The highest predictive accuracies were found in August, for *Festuca* (R^2 = 0.85; 7.64% of the mean), *Themeda* (R^2 = 0.86; 7.56% of the mean) and combined species (R^2 = 0.84; 9.27% of the mean).

Table 4 highlights the model performance using the 30% independent set, for individual species and pooled species dataset, based on variables, which only produced the best AGB estimation accuracies over time. Overall results indicate the potential of the SPLSR model in estimation accuracy, explaining above 70% of C3 and C4 species AGB variations over time. The model also produced highest estimation errors in May, compared to other periods. The results were also comparable to those produced using the 70% training dataset. For example, in February according to the 70% dataset, *Festuca* AGB was estimated with R^2 of 0.82 (9.84% of the mean); this was 0.79, with a RMSE of 13.32%. The performance of the model also varied over time using individual species dataset, as well as for pooled data. For example, using AGB data acquired in May, which had the highest measured values, the model showed lower estimation accuracies, compared to other periods. In May, *Festuca* AGB was estimated with an R^2 of 0.71, which was 20.22% deviation, whereas for *Themeda*, it was 0.70 with a RMSE of 21.02%. On the other hand, in February, *Festuca* AGB was estimated with an R^2 of 0.79 (13.32% of the mean), whereas *Themeda* was estimated with 0.76 (11.01% of the mean).

Table 3
Predictive accuracies using Sentinel 2 variables for estimating species AGB, over time.

Variables/Period	Festuca			Themeda			Combined species		
	R^2	RMSE (g/m^2)	RMSE (%)	R^2	RMSE (g/m^2)	RMSE (%)	R^2	RMSE (g/m^2)	RMSE (%)
Bands									
February	0.61	145.85	13.11	0.60	129.59	14.66	0.61	100.74	15.64
May	0.57	346.68	31.70	0.59	352.13	24.08	0.57	320.62	28.11
August	0.66	132.80	12.29	0.67	102.11	20.75	0.69	231.66	23.42
November	0.62	225.27	21.80	0.62	251.62	20.29	0.63	364.39	26.26
Indices									
February	0.76	91.19	10.49	0.74	99.62	15.11	0.73	96.80	10.64
May	0.70	299.95	22.05	0.69	246.95	16.51	0.70	267.71	23.15
August	0.78	108.53	11.89	0.78	96.36	15.86	0.77	192.23	15.78
November	0.73	185.98	18.99	0.76	223.60	15.35	0.71	313.72	19.63
Bands + Indices									
February	0.82	74.16	9.84	0.78	66.83	9.46	0.74	81.85	10.59
May	0.77	244.38	18.64	0.75	178.86	14.27	0.73	221.05	16.47
August	0.85	99.98	7.64	0.86	89.10	7.56	0.84	135.20	9.27
November	0.79	166.14	16.07	0.81	201.36	12.89	0.76	247.83	12.06

Table 4
Model validation results, using combined Sentinel 2 variables.

Period	Festuca			Themeda			Combined species		
	R^2	RMSE (g/m^2)	RMSE (%)	R^2	RMSE (g/m^2)	RMSE (%)	R^2	RMSE (g/m^2)	RMSE (%)
February	0.79	75.26	13.32	0.76	53.22	11.01	0.73	86.15	13.59
May	0.71	195.25	20.22	0.70	166.43	21.02	0.70	206.44	18.47
August	0.80	84.33	11.64	0.70	97.76	13.81	0.77	144.31	11.27
November	0.74	156.11	19.07	0.77	181.69	15.06	0.71	203.66	15.73

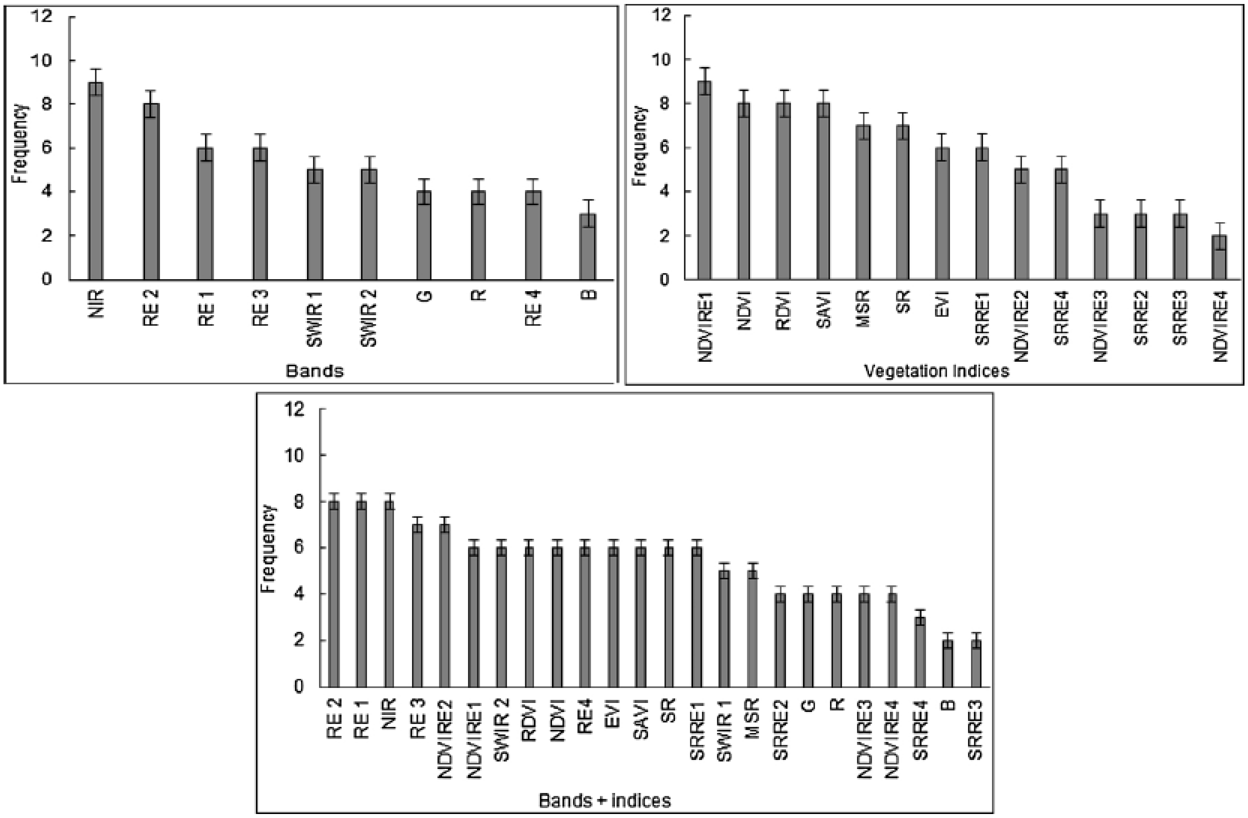

Fig. 4. Sentinel 2 derived variables frequencies in estimating species AGB, over time. Error bars show significant differences in variable frequency.

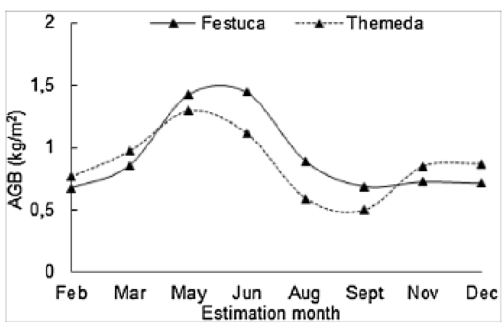

Fig. 5. Average species AGB variations over time (2016).

4.1. The importance of Sentinel 2 variables in species AGB estimation over time

The importance of Sentinel 2 variables in estimating species AGB, over time is graphically presented in Fig. 4. The Figure shows the frequencies of each variable, using each variable set for pooled dataset, over time. The use of spectral bands has shown that NIR (0.842 µm) had the highest frequency, followed by RE 2 (0.74 µm), whereas the visible blue had the lowest frequency. Red edge-based NDVI (NDVI derived using red edge band at 0.705 µm) showed the highest frequency, followed by the standard NDVI, whereas RE4-derived NDVI had the lowest frequency, when indices were used. The combined use of bands and vegetation indices showed that RE 1 (0.705 µm), RE 2 and the NIR had significantly the highest frequencies in their contribution in estimating AGB over time, whereas the simple ratio derived using red edge 3 had the lowest frequency.

4.2. *Temporal variations in species AGB using Sentinel 2 data*

Fig. 5 shows the derived AGB variations between the two species over time. The presented results are averaged AGB values, extracted using species GPS points. Overall, the two grass species showed variations in AGB over time. During the summer months of February, March, November and December 2016, higher AGB estimates were found for *Themeda* (C4), than *Festuca* (C3). There was however a shift in AGB variations between the two species, where higher estimates were found for *Festuca*, than *Themeda*, from May to September. Both species also showed a marked decrease in AGB, especially in August and September.

4.3. *The variability in AGB over time*

Fig. 6 illustrates the estimated variability in AGB over time for the study area during 2016, using Sentinel 2. Overall, AGB variations within the area exhibited temporal and spatial fluctuations and the sensor managed to capture these variations. Higher AGB were estimated in February, March, May, November and December, whereas during the mid-year, low AGB estimates were produced. The beginning of winter (May) had the highest AGB, compared to other months, whereas lowest estimates were after the winter fall (September).

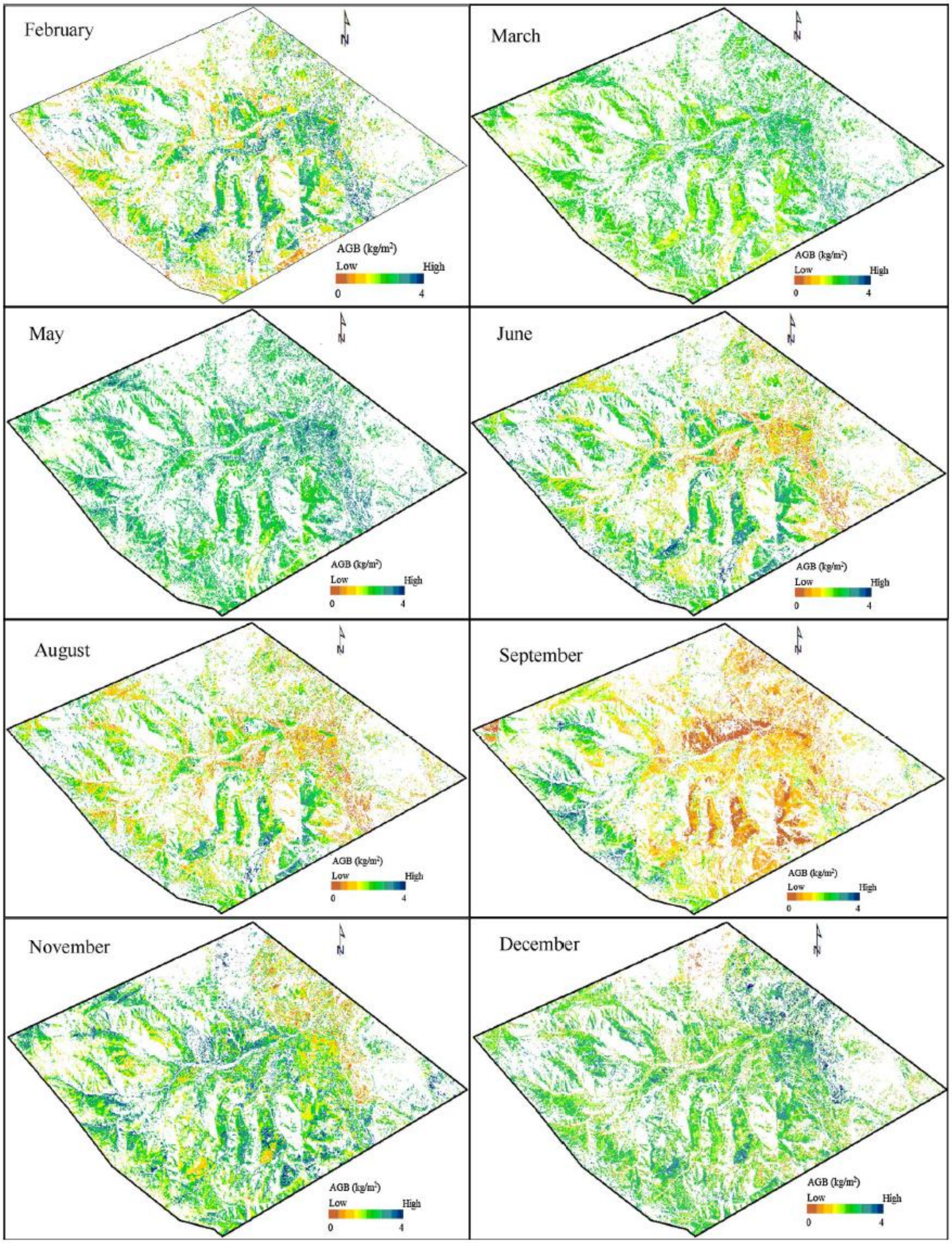

Fig. 6. The spatial and temporal variability of C3 and C4 grass species AGB over time.

5. Discussion

5.1. The importance of Sentinel 2 variables in estimating species AGB over time

Sentinel 2 variables have shown great potential in predicting C3 and C4 grasses AGB variations, over time. Among the most important variables in estimating species AGB were the red edge centred at 0.705 and 0.740 µm, derived indices, the NIR and SWIR spectral bands. For instance, the NIR band showed the highest frequency in its importance in estimating AGB and was also competitive among indices, when bands and vegetation indices were used. In accordance with results from this study, compelling studies (Mutanga and Skidmore, 2004; Ramoelo and Cho, 2014; Sharma et al., 2015) have reported the importance of red edge bands and derived indices in estimating AGB. It has been established that red edge variables are sensitive to species canopy AGB and chlorophyll concentration, when compared to other portions of the electromagnetic spectrum (Mutanga and Skidmore, 2004). This improves the competence of red edge bands and derived indices in estimating species AGB, over time. However, not all the Sentinel 2 red edge and derived indices were found to be important in species AGB prediction in this study. For example, red edge centred at 865 nm (band 8A) and derived indices have shown consistently poor importance in estimating species AGB, over time, with lower frequencies. The contribution of the SWIR may be attributed to its sensitivity to species water content, and this is variable between the two species, especially when *Themeda* (C4) becomes dormant, particularly in August. In consistence, Numata et al. (2008) revealed a significant correlation between grass AGB and water content, and suggested that the use of water related wavelength, improve AGB estimation accuracy. The study by Chen et al. (2011) also reported the importance of SWIR bands in estimating species AGB in the semi-arid rangelands of Idaho, using SPOT 5. In this regard, researchers might advocate for the development and use of Sentinel 2 SWIR-based indices in estimating C3 and C4 grass species AGB over time. The importance of NIR, as indicated by the highest frequency highlights its consistent, as well as its competence among indices in AGB estimation, over time. Previous studies (Lu et al., 2009; Price et al., 2002) have also found NIR to be a very important spectral portion in C3 and C4 grasslands monitoring.

On the other hand, the visible portion had the lowest frequencies in estimating species AGB over time. This shows that the visible bands are inconsistent and have limited potential in estimating C3 and C4 grass species AGB over time. The limited potential of visible bands in estimating AGB has been previously attributed to their sensitivity, for example, the review by Lu, (2006). These bands were reported to be less sensitive to species biophysical characteristics and AGB, hence they become insignificant and less competitive.

5.2. Species AGB prediction accuracies

The use of indices showed a marked increase in species AGB prediction accuracy over time, when compared to the use of individual bands. Indices have been reported to have better AGB prediction accuracies, when compared to the use of spectral bands (Sibanda et al., 2015a, 2017). This is due to the combination of different bands which improve their sensitivity, thereby boosting AGB prediction accuracy, when compared to individual bands which have limited sensitivity capacity. In confirmation, across C3 and C4 grasslands, studies which estimated AGB used vegetation indices, particularly NDVI (An et al., 2013; Rigge et al., 2013;

Tieszen et al., 1997). The broadband nature of the used sensors discouraged the use of spectral bands, which have been perceived to be insensitive to species biophysical properties, hence have low ability in estimating AGB. Thus Sentinel 2 extends the availability of variables for estimating C3 and C4 grasses AGB, which were previously limited to traditional indices.

Species AGB prediction accuracies was quite variable over time. For example, species AGB was predicted with relatively lower accuracies in May and November, than in February and August. This is a clear indication of the influence of seasonality on species AGB estimation accuracies, which might be associated with the amount of AGB available. In this study, lower AGB prediction accuracies in May are likely attributed to species phenology. Species phenology determines the accumulation of AGB and the subsequent estimation accuracy, using remote sensing data. This was also confirmed by the validation dataset, where the model showed lowest estimation accuracies in May. In May, *Themeda* had reached its peak, whereas *Festuca* was at its peak stage of growth, both species therefore had high density AGB. Field-based AGB measurements also confirmed that May had the highest AGB for both species. High AGB during peak stage of species phenology causes saturation problem and this might have challenged the estimation accuracy. Saturation due to high AGB at maximum productivity is one of the major problems associated with multispectral sensors in estimating species AGB. However, in February and November, although both species were active, they have not yet reached their peak, which implies limited saturation problem and therefore better accuracies, than in May. The influence of phenology and AGB variations on estimation accuracy was also noted by Ramoelo and Cho (2014) in north east South Africa, using Worldview 2 dataset. The study reported slightly higher prediction accuracies in July, which was characterized by lower AGB, when compared to March, which had higher species AGB. Similarly, the influence of high density AGB lowering estimation accuracy was also explored by Mutanga et al. (2012), using Worldview 2 dataset and random forest model.

Although the use of Sentinel 2 derived indices provided better estimation accuracies using data acquired during the study period, this study urges caution when estimating *Themeda* AGB during the winter fall, as the species and other C4 species starts to lose their vigour. Some of the indices used like NDVI are related to vegetation greenness and have been reported to have limited potential during low vegetation cover (for example, Butterfield and Malmström, 2009). In this regard, during February, May and November 2016, when both species were active, indices related to greenness remained applicable, despite saturation problems in May. However, in August, when C4 becomes less active and there is less vegetation cover, it is likely that soil reflectance interferes with species signal in *Themeda* dominated areas. Possibly, the use of other indices besides NDVI or the use of SWIR-based indices in estimating C4 AGB during low productivity stages is recommended.

5.3. Spatial variations in AGB over time

This study managed to depict the spatial variations of C3 and C4 dominated grassland AGB in KwaZulu-Natal, using Sentinel 2 multi-temporal dataset. The study confirms the potential of the Sentinel 2 sensor in estimating and mapping C3 and C4 AGB over time. This performance is the combined contribution of its spectral range, which constitute more and unique bands, as well as its 10 m spatial resolution. These characteristics are sensitive to C3 and C4 species physiological, morphological and phenological properties which improve the AGB prediction and variations. At a finer spatial resolution, subtle differences in AGB for different species are also better captured, with limited mixed pixel problem (Lu, 2006).

It was found that AGB across the study area exhibited spatial and temporal variations. This shows the influence of various factors governing AGB variations for C3 and C4 grass species across the area. The source of differences in AGB over time is contributed by the variations in species composition, growth, as well as climatic influence. For instance, reflecting on the distributional pattern of the grass species under study, the AGB variation maps are closely associated with the recognized distribution pattern of the target grass species (Fig. 1) or species composition and associated biophysical properties over time. In the present study area, *Themeda* is predominantly within the central, north east and eastern parts of the study area, which showed higher AGB during the summer months, when the species is most active and productive. In winter *Themeda* dries, due to harsh unfavourable conditions. This was also noticed especially in August, during field data collection. *Festuca* on the other hand has been reported to be active for most parts of the year, which promotes AGB availability, and during the field data collection the grass remained active, although it will not be as active as during early winter. In agreement, the study by Rigge et al. (2013) reported the effect of grass composition within a landscape on the spatio and temporal patterns of AGB.

The spatial distribution of AGB also coincided with the characteristics of the study area. For example, the far north east and eastern parts include communal areas, characterized by livestock grazing, as well as human disturbances, whereas the majority of the area is under conservation. Similarly, the communal area has more of *Themeda,* a high palatable grass that is favourable to livestock (Coughenour et al., 1985; Danckwerts et al., 1983), when compared to *Festuca*. *Themeda* is also recognized as an important source of fodder, fibre for paper, thatching and basketry. Consequently, this contributes to the loss of *Themeda* within the communal area, thereby lowering its AGB. The area under conservation showed consistently higher AGB during most times of the year. This is due to limited grazing and human disturbances, as well as the predominance of *Festuca* grass, which has been reported to be green for most part of the year. *Festuca* has also been identified as unpalatable and therefore unfavourable to grazers, compared to *Themeda*. This reduces grazing pressure in *Festuca* dominated landscapes. However, although it is not comparable to communal area, the conserved area also provide forage to a few small ungulate wildlife grazers (Joubert et al., 2017).

AGB variations also highlighted inter and intra-annual variability in climatic conditions, such as the reported seasonal rainfall and temperature, influencing the timing and amount of AGB accumulation. Although it was quiet variable across the study area, higher AGB was estimated during the summer months, whereas lower AGB was observed during winter months, particularly winter fall (August and September). Higher AGB may be primarily caused by the prevailing of favourable climatic factors, which boost species AGB production and accumulation. For instance, Morris et al. (2016) and Nel (2009) reported that the area receives summer rainfall, from November to March. This facilitates species growth and AGB production, during this period. This is most apparent for *Themeda,* which is most active in summer. In contrast, August and September showed a marked decrease in AGB across the area under study. This period is typically end of winter, associated with no rainfall (Everson et al., 1988), which limit plant growth, thereby lowering AGB production and accumulation for most parts of the area. This also indicates that the winter fall, present unfavourable conditions for AGB accumulation across the study area. A very limited number of studies have reported the AGB variations of C3 and C4 grass species within the area (Everson and Everson, 2016; Everson et al., 1985, 1988). These studies have reported high AGB during the summer months, compared to winter, using ground measurements. The influence of climate variability on C3 and C4 grasses AGB has been reported, for example, by the study done by Winslow et al. (2003) which reported significant response of C3 and C4 grass species AGB to water variability.

In relation to the general climate, for example rainfall pattern, which is one of the variables which influence AGB variations across the study area, few studies have detailed the typical rainfall received across the study area (Everson and Everson, 2016; Morris et al., 2016). The study by Morris et al. (2016) reported the mean annual rainfall range, based on longterm records from 1948 to 1994. They found that annual rainfall varied between 1020 and 1535 mm. Data acquired from the South African Observation Network has revealed that the study area received annual rainfall of approximately 1190 mm during the 2016 study period. This range falls within the long term record reported by previous studies; therefore AGB produced across the area might also be considered typical, varying from as low as less than 1 kg/m^2, to a maximum of 4 kg/m^2. However, although rainfall received falls within the long term average, the data used by Morris et al. (2016) might be considered inconclusive to draw solid conclusion about the rainfall pattern during the 2016 study period. In this regard, a comprehensive rainfall pattern, which includes recent recordings and other climatic variables which might influence species AGB across the area under study, is required.

6. Conclusion

Findings presented in this study demonstrated the spatial productivity of C3 and C4 grass species over time. This is crucial in determining the potential of C3 and C4 dominated grasslands as forage sources, their carrying capacity and in predicting the effects of global change on their productivity. The study also demonstrated the potential and strength of using the readily available Sentinel 2 data as an invaluable source of C3 and C4 grasses AGB information, for the proper and well-informed management at large areas. This is critical, especially in sub-Saharan Africa, where high-resolution remote sensing data availability remains a challenge for monitoring vegetation productivity and its response to environmental changes, over time. Results also demonstrated that SPLSR is a useful and a robust model for estimating C3 and C4 grass species AGB over time. Future studies may consider expanding to different rangelands or ecosystems, such as parks, communal areas and other protected areas, in which these grasses offer a wide range of services. It is also valuable to identify the productivity of different C3 and C4 grass species across the area.

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