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A potential to monitor nutrients as an indicator of rangeland quality using space borne remote sensing

A Ramoelo1,2, MA Cho, S Madonsela1, R Mathieu1, R van der Korchove2, Z Kasza2, E Wolf2

1Natural Resource and Environment, Council for Scientific and Industrial Research (CSIR), Pretoria, South Africa
2IGEAT, Université Libre de Bruxelles (ULB), Belgium

Email: aramoelo@csir.co.za

Abstract. Global change consisting of land use and climate change could have huge impacts on food security and the health of various ecosystems. Leaf nitrogen (N) is one of the key factors limiting agricultural production and ecosystem functioning. Leaf N can be used as an indicator of rangeland quality which could provide information for the farmers, decision makers, land planners and managers. Leaf N plays a crucial role in understanding the feeding patterns and distribution of wildlife and livestock. Assessment of this vegetation parameter using conventional methods at landscape scale level is time consuming and tedious. Remote sensing provides a synoptic view of the landscape, which engenders an opportunity to assess leaf N over wider rangeland areas from protected to communal areas. Estimation of leaf N has been successful during peak productivity or high biomass and limited studies estimated leaf N in dry season. The objective of this study is to monitor leaf N as an indicator of rangeland quality using WorldView 2 satellite images in the north-eastern part of South Africa. Series of field work to collect samples for leaf N were undertaken in the beginning of May (end of wet season) and July (dry season). Several conventional and red edge based vegetation indices were computed. Simple regression was used to develop prediction model for leaf N. Using bootstrapping, indicator of precision and accuracy were analyzed to select a best model for the combined data sets (May and July). The may model for red edge based simple ratio explained over 90% of leaf N variations. The model developed from the combined data sets with normalized difference vegetation index explained 62% of leaf N variation, and this is a model used to estimate and map leaf N for two seasons. The study demonstrated that leaf N could be monitored using high spatial resolution with the red edge band capability.

1. Introduction
The Global change consisting of land use and climate change could have huge impacts on food security and the health of various ecosystems, with a potential to exacerbate poverty especially in rural communities. Leaf nitrogen (N) is one of the key factors limiting agricultural production and ecosystem functioning or health. Leaf N (both trees and grasses) can be used as an indicator of rangeland quality which could provide information for the farmers, decision makers, land planners and managers. Leaf N is related to protein [1], and plays a crucial role in understanding the feeding patterns and distribution of wildlife and livestock [2,3]. Assessment of this vegetation parameter using conventional methods at landscape scale level is time consuming and tedious, while the production of detailed maps is simply impossible.

2 To whom any correspondence should be addressed.
Remote sensing provides a synoptic view of the landscape, which provides an opportunity to assess leaf N over wider rangeland areas from protected to communal areas. Successful estimation of leaf N was achieved using field and airborne imaging spectroscopy which are mainly applicable at local scale [4,5]. Vegetation indices have been widely used for the estimation of various biophysical (e.g. Leaf Area Index, biomass etc.) and biochemical (e.g. Leaf N, chlorophyll content etc.) parameters [5]. Recent studies demonstrated that, the use of red-edge based vegetation indices provide better estimates of leaf biochemicals [6,7]. The lack of red-edge bands in satellite multispectral sensors hindered the production of regional maps of leaf N. New space-borne sensors such as WorldView-2 and RapidEye designed with red-edge bands provide an opportunity for assessing leaf N at regional scale (over 5000 km²). Earlier work with RapidEye was reported by Ramoelo et al. [6] and Cho et al. [7]. Next year (2013), the European Space Agency (ESA) is planning to launch a new satellite (Sentinel-2), with spectral bands comparable to those of RapidEye and WorldView-2. ESA intends to provide data from Sentinel-2 for free, especially for Africa, which is expected to be a major step towards assessing nutrient status of vegetation. This will open the opportunity to routinely produce leaf N maps for various South African biomes. Further, the testing and development of this technology with high resolution sensor such as WorldView-2 will allow to better calibrate and validate nutrient models relying on coarser resolution sensors, available at more frequent time step and at subcontinent scale (e.g. Sentinel-2). A question to be investigated here is can new very high resolution multispectral imagery with red-edge bands such as WorldView 2 be used as to develop an approach to move towards regional assessment and monitoring of leaf N as an indicator of rangeland quality?

2. Study area
The selected study area is in the south-eastern part of South Africa (lowveld), located at 24°50′42.61″S, 31°21′18.66″E and 24°59′35.04″, 31°03′1.61″E. The study area stretches from the protected areas (Kruger National Park, Sabi Sands) and communal areas (Bushbuckridge area). The savanna ecosystem plays a crucial role in term of contributing to biodiversity conservation and livestock production. The study area is part of the transect where we are developing techniques to map various vegetation attributes such as grass biomass, woody biomass and species maps using multi-scale remote sensing data sets. Two geological types such as gabbro and granite, which underpins various soil fertility levels occurs in this study. The gabbro intrusions are associated with high soil fertility because it is easily eroded and rich in clay. Whilst, soil fertility is low because of in situ clay-forming potential is low [8]. Common grass species in this area are Setaria sphacelata, Panicum maximum, Heteropogon contortus, etc., while common tree species are Sclerocarya Birrea, Acacia nigrescence, Combretum species etc.

3. Data collection and sampling
WorldView 2 images for April and July 2012 were acquired and have a 2m x 2m spatial resolution. Studies such as Ramoelo et al. [6] and Skidmore et al. [9] showed that the best period to estimate grass nutrients is during peak productivity. As a result, we recently acquired March 2013 WorldView 2 image which because of limited time was not analysed for this study. The pre-processing was done, i.e. orthorectification and atmospheric correction using PCI Geomatica software. The atmospheric correction was done using the Atmospheric Correction for flat surfaces (ATCOR2) because the study area is characterized by flat to gentle undulating slopes.

Sample points for collecting grass and tree leaf samples were purposively located using the acquired WorldView 2 image. The fieldwork was undertaken within two weeks of image acquisition. For grasses similar points were visited and additional points were added in case the pre-selected points were burnt or overgrazed. For the dry season campaign, most of the tree leaf samples were collected in the riparian zones. In each sample point, a 6m x 6m plot of homogeneous grass cover was defined, and two –three subplots of 50cm x 50cm were randomly selected. In each subplot, grass samples were collected and data on dominant grass species was recorded. Within the vicinity of the plot, big trees of various species were identified and 5 leaves representative of the canopy were collected. The grass and tree leaf samples were dried (80°C for 24 hours) and taken to the laboratory for chemical analysis to retrieve leaf N at Bemlab PTY (LTD), Strand, Western Cape, South Africa.
4. Data analysis

Leaf spectra from WorldView 2 images for different dates were extracted corresponding to each sample GPS point with leaf N value. The 3 x 3 pixel window was used to extract the spectra corresponding to a plot size of 6m x 6m, for a 2m pixel size. The reflectance from 9 pixels was then averaged. Conventional and red-edge based vegetation indices such as simple ratio (SR) \[10\] and the normalized difference vegetation index (NDVI) \[11\] were computed. Several band combinations were used and based on the band combinations NDVI was named NDVI (855 and 605), NDVI1 (855 and 660nm), NDVI2 (950 and 605nm) and NDVI3 (950 and 660nm) and similarly for red edge based, NDVI-RE1 (855 and 725nm), NDVI-RE2 (950-725nm), NDVI-RE3 (725 and 605nm) and NDVI-RE4 (725 and 660nm). The same order was done for SR and similar bands were used as for NDVI, where SR1 will correspond to NDVI1, for example and so on. Vegetation indices were correlated with leaf N using basic simple regression with bootstrapping for validation. The best models were selected based on the coefficient of determination ($R^2$), root mean square error (RMSE) and the relative RMSE (RMSE/observed mean). The statistical analysis was implemented in R statistical programming language.

5. Results and discussion

Leaf N concentration variability was higher (mean=0.89, CV=67%) in May 2012 which is end of wet season and start of dry season as compared the dry season data sets in July (mean=0.83, CV=63%) (Table 1). Greener vegetations are likely to have higher nutrient concentrations as compared to drier ones because of active photosynthetic activities portraying the state or health of the vegetation. During dry periods the nutrients are generally translocated from the leaves to the roots. The high maximum values of leaf N are from trees as shown in Table 1. The combined data sets showed about 65% variability of leaf N which combines both dry and late wet season. More details of the descriptive statistics can be seen in Table 1.

| Data sets (%) | min | max | mean | STDEV | CV | No. of samples |
|---------------|-----|-----|------|-------|----|----------------|
| May-12        | 0.49| 2.63| 0.89 | 0.59  | 67 | 28             |
| Jul-12        | 0.40| 2.02| 0.83 | 0.52  | 63 | 41             |
| All (combined)| 0.40| 2.63| 0.89 | 0.58  | 65 | 69             |

$STEDEV = \text{standard deviation, CV=coefficient of variation}$

Red-edge based simple ratio (SR-SR3) using bands centred at 605 and 725nm explained over 90% of leaf N variation in the May model as compared to 61% in July 2012 model (Table 2). The model developed from the combined or pooled data sets (May and July) explained 62% of leaf N variation with a RMSE yielding 43% of the observed mean, which is two-times higher than RRMSE achieved by the May model. Similar results were achieved by Ramoelo et al. [6], demonstrated that a good prediction of leaf N can be achieved in peak productivity, and Knox et al. [12] also showed a possibility to estimate leaf N in dry season but the estimation accuracy is relatively low.

Table 2: Performance of various data sets and vegetation indices to predict leaf N.

| Best Models | $R^2$ | RMSE (%) | RRMSE (%) | Estimate | Intercept | $P$   |
|-------------|-------|----------|-----------|----------|-----------|-------|
| May-12: SR-RE2 | 0.93  | 0.1524   | 17        | 0.5451   | 0.3620    | < 0.05 |
Figure 1 shows the best relationships obtained for each season and combined data sets. Clusters of low values depicted in figure 1 are mainly for grass. The May model shows low values deviating from a regression line which shows that vegetation indices are not only related to leaf N, may be with biomass as well. Phenology is a major driver of this outcome [13], especially when using vegetation indices which depend on the vegetation greenness. The results show that the models are driven by the tree leaf N values in winter (July) than the grass. Most trees especially evergreen ones tap water from underground during dry season, sustaining greenness throughout, than the deciduous trees which shed their leaves during dry season.

Spatial distribution of high leaf N values is evident in May (Figure 2) as compared to July map (Figure 3). The high leaf N values in May (Figure 2) depicted by red colour are trees and shrubs as evident in the riparian zones. While in July (Figure 3), high leaf N values are concentrated in the riparian or riverine areas which are mainly associated with trees than grass. These patterns are mainly influenced by the greenness of vegetation which could be linked to rainfall [14]. The riverine areas exhibit high leaf N values in both April/May and July, which could be associated with the deposited soil nutrients from the crest [8] and also availability of water in the rivers during winter season.
The key question investigated in this study was “can new high spatial multispectral imagery with red-edge bands such as WorldView-2 be used to develop an approach to move towards regional assessment and monitoring of leaf N as an indicator of rangeland quality”? The study demonstrated that leaf N can be estimated using vegetation indices in dry and wet season. Season specific analysis showed that April or May models performed better than the dry season one (July model). This study fulfils what was achieved by Ramoelo et al. [6], Skidmore et al. [9] as well as Knox et al. [12].

6. Conclusions
Prediction of leaf N across season is possible using WorldView-2 satellite imagery with the red edge band capability. The assessment and monitoring of Leaf N as an indicator of rangeland quality can be developed using combined or pooled data sets for different seasons. This study provides a basis for rangeland monitoring and assessment at even larger scales using data sets like the upcoming Sentinel-2 with red edge capability.
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