ESTIMATING GRASS NUTRIENTS AND BIOMASS AS AN INDICATOR OF RANGELAND (FORAGE) QUALITY AND QUANTITY USING REMOTE SENSING IN SAVANNA ECOSYSTEMS

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ABSTRACT

Grass quality and quantity information plays a crucial role in understanding the distribution, densities and population dynamics of herbivores (i.e. livestock and wildlife). Leaf nitrogen (N) and biomass (g/ m^2) are indicators of grass quality and grass quantity, respectively. The objective of the study is to estimate and map leaf N and biomass as an indicator of rangeland quality and quantity using vegetation indices derived from one RapidEye image taken at peak productivity. The study was undertaken in the north-eastern part of South Africa, in a transect extending from protected areas such as Kruger National Park and a privately owned game reserve to the communal areas of Bushbuckridge. Field work was undertaken to collect data on biomass and grass samples for retrieving leaf N, in April 2010, same time with image acquisition. RapidEye image was atmospherically corrected using atmospheric correction software for flat surfaces (ATCOR 2). Environmental or ancillary data sets were also collected from various sources as to develop an integrated modeling approach with the remotely-sensed indices. Commonly used vegetation index such as simple ratio was used exploiting a new red-edge band embedded in the RapidEye sensor. Leaf N regression models were developed using simple regression. Biomass (g/m^2) prediction models were developed by applying bootstrapped stepwise regression using a combination of vegetation index and environmental or ancillary variables. Simple ratio (SR54) based on red-edge band produced higher grass N estimation accuracy. For the biomass estimation, vegetation indices produced poor results explaining less than 15% of variation. Biomass estimation was significantly improved to 27% of explained biomass variation by integrating vegetation index (SR54) and ancillary data. The latter approach is crucial because biomass is influenced by various environmental variables, which therefore play a crucial role in model development. The study demonstrated a potential of forage quantity and quality estimation using new high spatial remote sensing data with the red edge band. Integrating vegetation indices and ancillary data provides an opportunity to map grass biomass during peak productivity. Forage quality and quantity information is crucial for planning and management of grazing resources.

INTRODUCTION

Africa has a long history of pastoralism (livestock grazing) which has been a major source of livelihoods. Most of African people used to be nomadic, i.e. seasonal movement in search of greener pastures for their livestock. Even today, livestock production which is dependent on grass or pasture quality and quantity is still a major source of income in the rural economy (Shackleton et al. 2002). Pasture quality can be defined by leaf nutrient content (e.g. nitrogen-N), while quantity can be defined by biomass (mass per unit area). Grass quality and quantity are pertinent to understanding the distribution, feeding patterns and population dynamics of livestock and wildlife (Drent and Prins 1987; McNaughton 1988) and crucial to inform decision making regarding the planning and management of savanna rangelands. Therefore, spatial information about grass quality and quantity is needed to guide farmers, resource managers and land use planners in sustainable management of their grazing land.

Estimation and mapping of grass nutrients and biomass have been successful using mostly laboratory, field and imaging *or* airborne spectrometry or hyperspectral. The techniques for estimating vegetation parameters using remote sensing fall into two categories;

- statistical or empirical analysis using vegetation indices (Haboudane et al. 2004), full spectrum analysis (Ramoelo et al. 2011), specific absorption features (Knox et al. 2011), as well as integrated modeling approach (remote sensing and environmental variables) (Knox et al. 2011; Ramoelo et al. 2012)
- inversion of radiative transfer models (Darvishzadeh et al. 2008).

Grass nutrients have rarely been mapped at the regional scale because of the lack of satellite-based sensors that sample reflected electromagnetic energy in the red-edge region which is sensitive to foliar chlorophyll and nitrogen (N). Medium resolution satellites are also generally not suitable to discriminate grass and tree signals in heterogeneous and patchy savannas. The emergence of high resolution multispectral sensors with red-edge information such as RapidEye, SumbandilaSat, and Sentinel-2 (to be launched 2013) provides new opportunities for rangeland quality and quantity assessment at regional level. A challenge in estimating foliar biochemical concentrations, for example N, using indices is the interaction effects between N and biomass (Skidmore et al. 2010). Studies argue that if foliar biochemical estimation is not biomass corrected, then the interaction between N and biomass is likely to compromise the estimation of N (Plummer 1988; Skidmore et al. 2010). The solution to this challenge is to predict N during peak productivity (Skidmore et al. 2010), when multispectral indices fail to estimate biomass because of saturation problems (Mutanga and Skidmore 2004). Thus, another challenge is to improve on the estimation of biomass at peak productivity as to be able to assess both the nutrient and biomass status from a single image. Few studies have tested the applicability of the integrated modelling, i.e. the use of remote sensing and environmental or ancillary variables (Knox et al. 2011; Ramoelo et al. 2012), to estimate foliar biochemical concentrations or biomass. We hypothesized that the prediction of biomass could be possible through the integration of indices and environmental variables at peak productivity. The objectives of the study are twofold; (1) to estimate and map grass N using vegetation indices as an indicator of rangeland quality and (2) to estimate and map biomass as indicator of rangeland quantity by integrating remote sensing and ancillary variables.

MATERIALS AND METHODS

Study area and data collection

The study area is located in the north-east of South Africa and covers part of the Kruger National Park (KNP), SabiSands and Bushbuckridge communal rangelands (Figure 1). Field work was undertaken in April 2010, the same month than the acquisition of the RapidEye satellite image. The areas along the main roads covering the study area were purposively selected for the field sampling, also considering the underlying geological strata. The road sampling technique was preferred since penetration into the savanna landscape was constrained by management and logistical restrictions. Buffers of 300 m were created on both sides of these roads using ArcGIS software (ESRI, USA). Within the buffer polygons random sample points were generated using the ArcGIS add-on called Hawth tools. Once in the field location, 51 plots were placed in relatively large areas with homogeneous grass to avoid the possible contamination of the tree signal on the grass signal. In each plot of 20m x20 m, two subplots of 0.5m x 0.5m were randomly placed and the following data were collected percentage composition of green or photosynthetic vegetation (PV), non-PV and bare soil , grass samples were cut and weighed to determine green or wet biomass (g/m^2), henceforth referred to as biomass.

Grass materials were dried at 80^0C for 24 hours, and then sent for chemical analysis to retrieve leaf N (% of dry matter) to the South African's Agricultural Research Council, using wet digestion techniques. Foliar N was multiplied by PV to derive a canopy N which is a proxy of structure and foliar N (N*PV). The RapidEye data were acquired in April 2010. The sensor is a multispectral push broom imager with a spatial resolution of 6.25 m and captures data in the spectral bands: blue (440-550 nm), green (520-590 nm), red (630-685 nm), red edge (690-730 nm), and near infrared (760-850 nm). Surface reflectance data were retrieved using the atmospheric and topographic correction software (ATCOR 2) implemented in the IDL Virtual Machine (Richter 2011). ATCOR 2 models reflectance for flat surfaces, which was considered sufficient because the study area is not characterized by very rugged terrain. Ancillary or environmental variables used included; mean annual temperature and precipitation (www.worldclim.com), altitude (STRM 4.1, http://srtm.csi.cgiar.org/), distance to rivers (river layer from South African National Botanical Institute-SANBI), slope and aspect were derived from altitude data using ArcGIS (ESRI, USA).

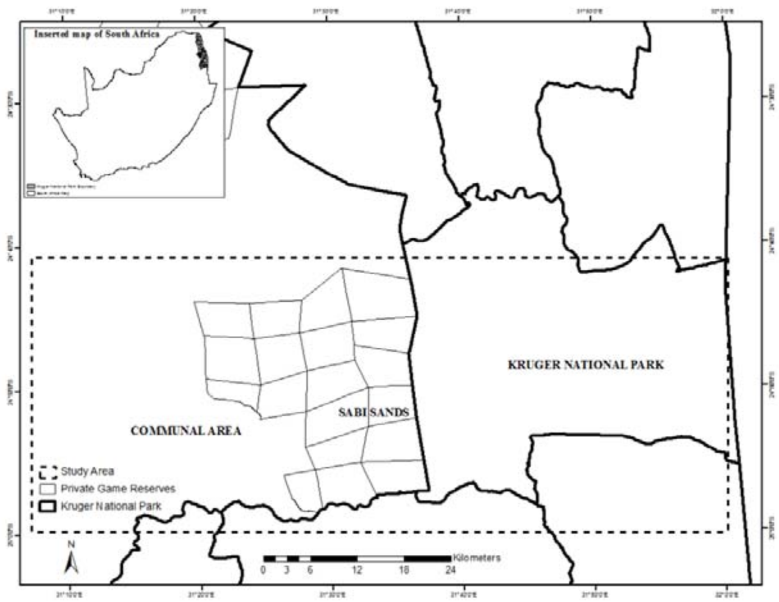

Figure 1: Study area map showing the north-eastern part of South Africa

Data analysis

For foliar N prediction, a commonly used simple ratio vegetation index was used, but we assessed one conventional version based on the NIR and red bands (SR53) and one version using the red-edge band (SR54) as to take full benefit of the RapidEye data. Foliar N prediction models were developed using simple regression in combination with the vegetation indices. Biomass (g/m^2) prediction models were developed by applying stepwise regression using a combination of vegetation indices and environmental or ancillary variables. Stepwise multiple linear regression is the commonly used technique to estimating vegetation parameters (Kokaly and Clark 2009; Ramoelo et al. 2012). Best models were applied to the image to create the biomass map. The models were validated using bootstrapping, which is an unbiased validation technique, because we had a small sample size. All the models were developed using R programming project for statistical computing.

RESULTS AND DISCUSSION

The descriptive statistics of field data showed that the mean, min and max values of the canopy nitrogen was 63, 35 and 119 (unit-less), and leaf N, 0.84, 0.53 and 1.44 (%), respectively. For biomass, mean, min and max values were 800, 284 and 1536 g/m^2, respectively. The coefficient of variance indicated that there is relatively high variation or dispersion (20-25 %) for leaf and canopy N and 38% percent for biomass. The relative high variation or dispersion of grass N and biomass can be attributed to the heterogeneous nature of savannas, influenced by several biophysical and climatic drivers (Venter et al. 2003)

The simple ratio (SR54) based on red-edge (4) and near-infrared (5) bands produced significantly higher canopy N estimation accuracy (bootstrapped: R^2=0.45, RMSE=13, 20% of mean, p<0.05), compared to the conventional index (SR53) (bootstrapped: R^2=31, RMSE=15, 24% of mean), using is the red band (3) (Figure 2). Similar trends were observed for foliar N, and red edge based index was significant (bootstrapped: R^2=0.15 and 0.23, for the conventional and red edge based index, respectively) (Figure 2). Red-edge position is known to be insensitive to background effects, and highly correlates to chlorophyll (Darvishzadeh et al 2008). Chlorophyll relates positively with leaf N (Yoder and Pettigrew-Crosby 1995), which permits a prediction of leaf N using vegetation indices. The disadvantage of using vegetation indices to predict leaf N, is that the relationship between leaf chlorophyll and N deteriorate as the leaf senesce (Wang et al. 2009). Figure 3 shows the nutrient maps. The distribution of nutrients approximates well the various geological types of the study area, with the highly nutritious grasses found in basalt-derived soils and the low nutritious grasses found in the granitic-derived soils. Geology and soil are known to be an important driver of the nutrient content of the grass in savanna ecosystems (Venter et al. 2003; Scholes 2003).

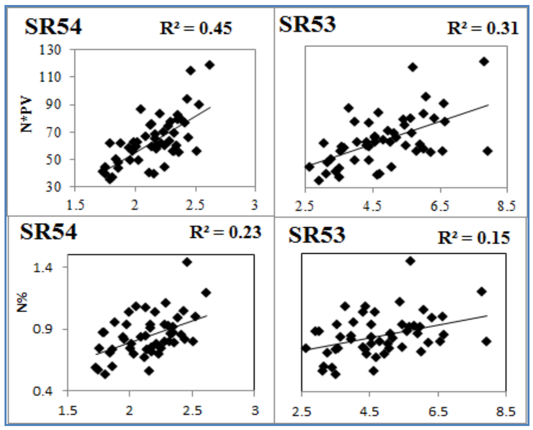

Figure 2: Scatterplots showing the performance of red-edge based vegetation indices (*Top and Bottom Left*) as compared to conventional ones (*Top and Bottom Right*).

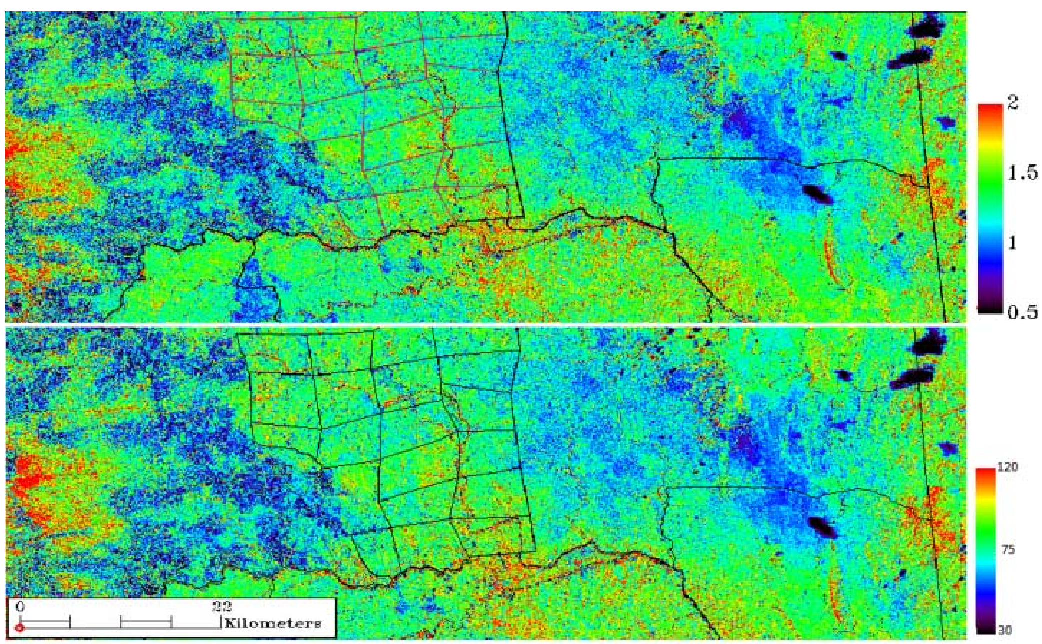

Figure 3: Maps showing a spatial distribution of foliar (*Above*) and canopy N (*Below*) derived from vegetation indices.

For the biomass estimation, vegetation indices produced non-significant results explaining less than 15% of variation. The result were improved by integrating the vegetation index SR54 and environmental variables (Bootstrapped: R^2=0.27, RMSE=264g/m^2, 33% of mean) using stepwise regression. SR54, precipitation and altitude were found to be significant in explaining the variation of grass biomass across the study area. There is an evident east-west gradient of precipitation and altitude in the study area which plays a role in the spatial distribution of biomass. Further, low lying areas are likely to have high biomass than the uplands, because the low lying areas have higher soil fertility with accumulation of clay materials (Scholes 2003). As for the nutrient maps, and as expected the more fertile soils derived from basalt geological type were found to have a higher biomass as compared to the granitic-derived soils (Figure 4). Figure 4 showed gabbro to have lower biomass and N than granite, similar results for leaf N was attained by Grant and Scholes (2006). This could be attributed to the occurrence of high leaf N content in the bottomlands of the granitic areas (Scholes et al 2003). Basalt parent materials have higher clay content as compared to granitic type of soils (Venter et al. 2003). The spatial distribution of biomass is generally related to the geological types (Figure 5). The results also show that protected area have higher biomass than communal areas (Figure 5), see blue patches on the western part of the map). Communal areas in this area are subjected to overgrazing. Several studies argued that there is land degradation in this area, which could attributed to lack of planning and management of this rangelands.

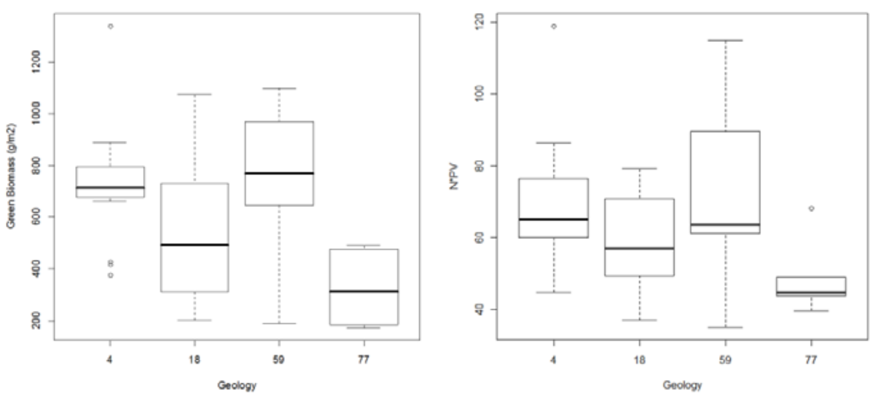

Figure 4: Boxplots indicating varying grass biomass (left) and N (right) over geological types (18=granite, 77=gabbro, 59=shale, 4=Basalt)

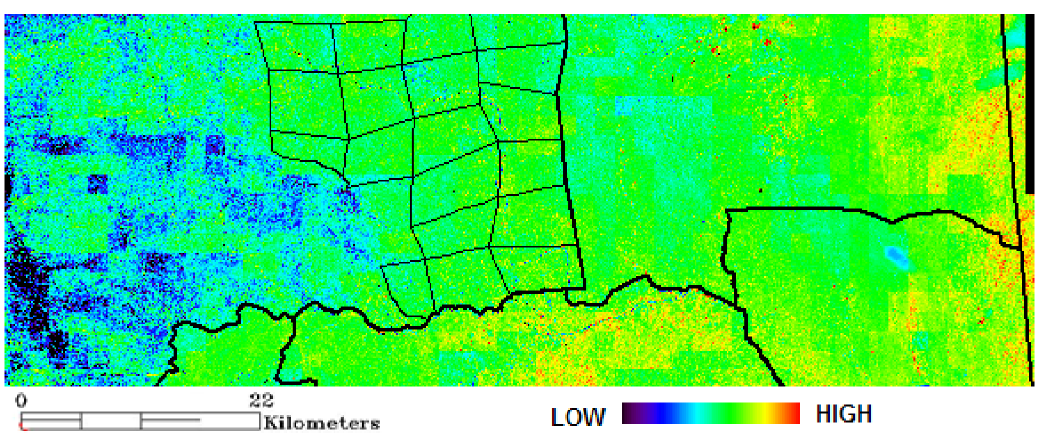

Figure 5: spatial distribution of green biomass (g/m^2) over Great Kruger National Park.

Vegetation indices yielded poor results in estimating biomass, because of known saturation problems especially during a period of peak productivity. During this period, the amount of light that can be absorbed in the red region of the spectrum reaches a plateau (Tucker 1977; Mutanga and Skidmore 2004). Additionally, the NIR reflectance continue to increase, because addition of new leaves influence the multiple scattering within the canopy (Kumar et al. 2001). This results into smaller change in the vegetation index (e.g. NDVI or SR), explaining and causing the poor relationship with biomass. The concentration of foliar N, in particular, reaches a maximum during the active growth during the wet season (Tolsma et al. 1987). Therefore, it is assumed that the foliar N dominates the reflectance during maximum biomass, and it is during this period that we can successfully estimate foliar N (Skidmore et al. 2010). On the other hand, combining vegetation index and ancillary data improves the biomass estimation, which partially addresses the problem of saturation or poor correlation with indices. Even though ancillary variables improve the estimation of biomass, their quality needs to be assessed in order to understand error propagation.

CONCLUSIONS

- The study demonstrated a potential to estimate rangeland quality using new high spatial resolution remote sensing data with the red edge band.
- Integrating vegetation index and environmental factors improves rangeland quantity estimation during peak productivity.

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REFERENCE

Cho, M.A. and Skidmore, A.K. (2006) A new technique for extracting the red edge position from hyperspectral data : the linear extrapolation method. *Remote sensing of environment*, 101. 181-193

Darvishzadeh, R., Skidmore, A., Schlerf, M. & Atzberger, C. 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.

Drent, R. H. & Prins, H. H. T. 1987. *The herbivore as prisoner of its food supply*. In: Andel, J. V., Bakker, J. & Snydon, R. W. (eds.) Disturbance in grasslands: Species and Population Responses. Dordrecht: Dr. W. Junk Publishing Company.

Haboudane, D., John, R., Millera, J. R., Tremblay, N., Zarco-Tejada, P. J. & Dextraze, L. (2002). Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. *Remote Sensing of Environment*, 81 (2-3), 416-426.

Grant, C., Scholes, M. 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.

Knox, N. M., Skidmore, A. K., Prins, H. H. T., Asner, G. P., van der Werff, H. M. A., de Boer, W. F., van der Waal, C., de Knegt, H. J., Kohi, E. M., Slotow, R. & Grant, R. C. 2011. Dry season mapping of savanna forage quality, using the hyperspectral Carnegie Airborne Observatory sensor. *Remote Sensing of Environment*, 115 (6), 1478-1488.

Kumar, L., Schmidt, K. S., Dury, S. & Skidmore, A. K. 2001. *Imaging Spectroscopy and Vegetation Science*. In: VAN DER MEER, F. D. & DE JONG, S. M. (eds.) Image Spectroscopy. Dordrecht: Kluver Academc Publishers.

McNaughton, S. J. 1988. Mineral nutrition and spatial concentrations of African ungulates. *Nature*, 334, 343-345.

Mutanga, O. & Skidmore, A. K. 2004. Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International Journal of Remote Sensing*, 25 (19), 3999 - 4014.

Plummer, S. E. 1988. Exploring the relationships between leaf nitrogen content, biomass and the near-infrared/red reflectance ratio. *International Journal of Remote Sensing*, 9 (1), 177-183.

Ramoelo, A., Skidmore, A.K., Schlerf, M, Mathieu R, Heitkonig I.M.A. 2011. Water - removed spectra increase the retrieval accuracy when estimating savanna grass nitrogen and phosphorus concentrations. *ISPRS journal of photogrammetry and remote sensing*, 66, 408-417.

Ramoelo A, Skidmore A.K, Cho M.A. Schlerf M. Mathieu R. Heitkönig I.M.A. 2012. Regional estimation of savannah grass nitrogen using red edge band of the RapidEye sensor, *International Journal of Applied Earth Observation and Geo-information (JAG)*, 19, 151-162

Scholes, R. J., Bond, W. J. & Eckhardt, H. C. 2003. *Vegetation Dynamics in the Kruger Ecosystem*. In: du Toit, J. T., Rogers, K. H. & Biggs, H. C. (eds.) The Kruger Experience : Ecology and Management of Savanna Heterogeneity. London: Island Press.

Shackleton, S. E., Shackleton, C. M., Netshiluvhi, P. R., Geach, B. S., Ballance, A. & Fairbanks, D. H. K. 2002. Use patterns and value of savanna resources in three rural villages in South Africa. *Economic Botany*, 56 (2), 130-146.

Skidmore, A. K., Ferwerda, J. G., Mutanga, O., van Wieren, S. E., Peel, M., Grant, R. C., Prins, H. H. T., Balcik, F. B. & Venus, V. 2010. Forage quality of savannas -- Simultaneously mapping foliar protein and polyphenols for trees and grass using hyperspectral imagery. *Remote Sensing of Environment*, 114 (1), 64-72.

Tolsma, D. J., Ernst, W. H. O., Verweij, R. A. & Vooijs, R. 1987. Seasonal Variation of Nutrient Concentrations in a Semi-Arid Savanna Ecosystem in Botswana. *Journal of Ecology*, 75 (3), 755-770.

Tucker, C. J. 1977. Asymptotic nature of grass canopy spectral reflectance. *Applied Optics*, 16 (57-1151).

Venter, F. J., Scholes, R. J. & Eckhardt, H. C. (eds.) 2003. *Abiotic template and its associated vegetation pattern*, London: The Island Press.

Wang, Y., Wang, F., Huang, J., Wang, X. & Liu, Z. 2009. Validation of artificial neural network techniques in the estimation of nitrogen concentration in rape using canopy hyperspectral reflectance data. *International Journal of Remote Sensing*, 30 (17), 4493 - 4505.

Yoder, B. J. & Pettigrew-Crosby, R. E. 1995. Predicting nitrogen and chlorophyll content and concentrations from reflectance spectra (400-2500 nm) at leaf and canopy scales. *Remote Sensing of Environment*, 53 (3), 199-211.