Continuum-removed absorption features estimate tropical savanna grass quality *in situ*

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ABSTRACT

The remote sensing of grass quality as determined by nitrogen, phosphorous, potassium, calcium and magnesium concentration is critical for a better understanding of wildlife and livestock feeding patterns. Although remote sensing techniques have been proven useful to assess the concentration of foliar biochemicals under controlled laboratory conditions, more investigation is required to assess their capabilities at field level where inconsistent results have been obtained so far. We investigated the possibility of estimating the concentration of biochemicals in a savanna rangeland using spectral reflectance of five grass species. Canopy spectral measurements were taken in the field using a GER 3700 spectroradiometer. We tested the utility of using three methods: (i) continuum removed derivative reflectance (CRDR), (ii) band depth (BD) and (iii) band depth ratio (BDR) derived from continuum removed absorption features to estimate canopy N, P, K, Ca and Mg. Stepwise linear regression was used to select wavelengths from the absorption feature based methods. Using the training data set, the three methods could explain the variation in foliar nutrient concentration with R^2 values ranging from 0.43 to 0.80. Results were highest from CRDR data, which yielded R^2 values of 0.70, 0.80, 0.64, 0.50 and 0.68 for N, P, K, Ca and Mg, respectively. Predicting biochemicals on a test data set using regression models developed from a training data set resulted in R^2 values ranging from 0.23 to 0.70 between the measured and predicted biochemicals. The method may be extended to data acquired by airborne and space borne imaging spectrometers to estimate and to ultimately map the concentration of macronutrients in tropical rangelands.

KEY WORDS

Field spectra, absorption features, bootstrapping, continuum removal, and Kruger National Park

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1. INTRODUCTION

The remote sensing of macronutrients (nitrogen, phosphorous, potassium, calcium and magnesium) that largely determine grass quality is critical for a better understanding of wildlife and livestock feeding patterns. Macronutrients are mainly responsible for plant growth, development and health. Therefore, they determine nutritional quality for herbivores (Salisbury and Ross, 1985). To prevent malnutrition and diseases, wildlife exhibit preference for certain sites and certain plant species or communities based on quality (Muya and Oguge, 2000). Therefore, the remote sensing of grass quality is important to explain the distribution and feeding patterns of wildlife and livestock (Styles and Skinner, 1997; van Soest, 1994).

The remote sensing of foliar biochemicals developed rapidly from the late 1970s (Curran *et al.*, 1995; Peterson *et al.*, 1988; Wessman, 1994; Yoder and Pettigrew-Crosby, 1995), mainly using methods from laboratory near-infrared spectroscopy (NIRS) (Marten *et al.*, 1989; Norris *et al.*, 1976). The extension of the empirical laboratory NIRS to estimate biochemicals at canopy level has not been very successful to date (Curran *et al.*, 2001; Kumar *et al.*, 2001). This is because the presence of water in fresh canopies masks the biochemical absorption features especially in the short wave infrared (Clevers, 1999; Kokaly and Clark, 1999). In addition, leaf orientation, soil background effects as well as atmospheric absorption further complicate the remote sensing of biochemicals at field level (Asner *et al.*, 2000). As a result, studies that used NIRS methods such as multiple linear regressions to predict canopy chemistry yielded inconsistent results when applied across different vegetation types (Grossman *et al.*, 1996). In addition, NIRS based techniques such as stepwise regression suffer from problems of overfitting, especially when more wavebands than samples are used (Curran *et al.*, 2001).

To overcome these problems, Kokaly and Clark (1999) applied a refined method (band depth analysis of absorption features) that enhances and standardizes known chemical absorption features in order to minimize the effect of spectral variability that is independent of the biochemical concentration. Like NIRS, this method uses stepwise regression. However, the effect of overfitting is minimized by concentrating on known absorption pits that are enhanced by continuum removal (Clark and Roush, 1984). The band depth analysis method showed strong correlation (r^2 = 0.95) with nitrogen concentration measured on dried ground plant material. Recently, Curran *et al.*, (2001) applied the Kokaly and Clark methodology on 12 biochemicals with high accuracy. However, the above studies were conducted under controlled laboratory conditions. The extension of the method to field level has not been made to our knowledge. In addition, only a few studies have attempted to estimate the foliar nutrient status of potassium, phosphorous, magnesium and calcium.

In this study, we aimed at improving and extending the band depth analysis method to estimate the concentration of macronutrients in grass (nitrogen, phosphorous, potassium, calcium and magnesium) measured at field level in the Kruger National Park, South Africa. Apart from the short wave infrared absorption features used by Kokaly and Clark, we added the two major absorption features located in the

visible region, where the effect of water is minimal. A modified first derivative reflectance approach was also developed and tested.

2. MATERIALS AND METHODS

2.1 The Study Area

The study area was located in the Northern plains of the Kruger National Park in South Africa. The Kruger National Park comprises an area of 1 948.528 km^2. A strip of 4 by 25 km stretching from the west ($22^0 49'$ S and $31^0 01'$ E) to the east ($22^0 44'$ S and $31^0 22'$ E) covering granitic and basaltic formations was selected. Generally, the site is flat especially on the eastern part, which is underlain by basalt rocks. The area is covered by open grassland in the east, mixed mopane and grass in the basalt – granite transition and dense woodland in the granite area.

Stratified random sampling with clustering was adopted in this study. The area was stratified into open grassland in the basalt, mixed woodland and woodland in the granite area. Coordinates (x y) were randomly generated in each polygon to select plots. To increase the number of samples in a time and labour constraint situation, extra two samples were clustered at least 100 m from the initially generated plots. A total of 96 samples were collected. Each plot covered 20 m by 20 m. The dominant species (covering at least 30 % of the area) in each polygon were recorded.

2.2 Canopy Spectral Measurements

Canopy spectral measurements were taken for the dominant species in each plot using a GER (Geophysical and Environmental Research Corp.) spectroradiometer. The GER 3700 is a three dispersion grating spectroradiometer using Si and PbS detectors with a single field of view. The wavelength range is 350 nm - 2500 nm with a resolution of 1.5 nm in the 350 nm - 1050 nm, 6.2 nm in the 1050 nm - 1900 nm range and 9.5 nm in the 1900 nm - 2500 nm range. The fiber optic sensor, with a field of view of 10 º was pointed on the target at nadir position from about 1 m height for each spectral measurement. The radiance was converted to reflectance using scans of a Spectralon 100 % reference panel. Every target measurement was made after measuring the reference (Spectralon) panel to control for possible variations in illumination conditions. The resulting spectrum was determined as an average of 25 spectral measurements per species in each plot. The fieldwork was contacted at the beginning of the dry season (from mid April to mid May of 2002) to maximise a large number of bright sunshine days. Measurements were taken on clear sunny days at high sun angle between 11:30 A.M and 2:00 P.M.

2.3 Biochemical Analysis

The spectrally measured grass species in the plots were clipped and oven dried at 70º C for 24 hours. Plant tissue analysis was done in South Africa using the wet extraction techniques. Atomic Absorption flame spectroscopy using air-acetylene was used for the detection of K, Ca, Mg and Na. The detection of N and P was based on the colometric method. For P detection, the phosphomolybedenum complex was read at 660 nm and for N detection, ammonia-salicylate complex was read at 640 nm.

2.4 Data Analysis

2.4.1 Absorption features

Six known chemical absorption features were selected for this study (Table 1). These include the chlorophyll absorption features in the visible domain ($R_{470 - 518}$ and $R_{550 - 750}$), which have been found to be related to nitrogen concentration and other bio chemicals on fresh standing canopies (Mutanga *et al.*, 2002) as well as on dried ground plant material (Curran *et al.*, 2001) and also short wave absorption features ($R_{1116 - 1284}$, $R_{1634 - 1786}$, $R_{2006 - 2196}$ and $R_{2222 - 2378}$) that have hitherto been applied on dried plant material (Curran *et al.*, 2001; Kokaly and Clark, 1999). Kokaly and Clark (1999) as well as (Curran *et al.*, 2001) used chemical absorption features located in the short wave infrared for three and twelve biochemicals respectively, but emphasized that the effect of water should be computationally removed to an accuracy of within 10 %. In order to minimise the effect of water, data was collected during the early dry season in May 2002 when standing biomass was still high but most of the grass was dry.

Table 1. Location of the absorption ($R_{\lambda a - \lambda b}$) features used in this study

Absorption feature	Short wavelength end	Long wavelength end
$R_{408 - 518}$	408	518
$R_{550 - 750}$	550	750
$R_{1116 - 1284}$	1116	1284
$R_{1634 - 1786}$	1634	1786
$R_{2006 - 2196}$	2006	2196
$R_{2222 - 2378}$	2222	2378

Continuum removal was applied to the selected absorption features. Continuum removal normalizes reflectance spectra in order to allow comparison of individual absorption features from a common baseline (Kokaly, 2001). The continuum is a convex hull fitted over the top of a spectrum to connect local spectrum maxima. The continuum-removed reflectance $R'_{(\lambda)}$ is obtained by dividing the reflectance value $R_{(\lambda)}$ for each waveband in the absorption pit by the reflectance level of the continuum line (convex hull) $Rc_{(\lambda)}$ at the corresponding wavelength. Stated formally:

$$R'_{(\lambda i)} = \frac{R_{(\lambda i)}}{R_{c(\lambda i)}}. \quad (1)$$

The first and last spectral data values are on the hull and therefore the first and last values of continuum-removed spectrum are equal to 1. The output curves have values between 0 and 1, in which the absorption pits are enhanced (Schmidt and Skidmore, 2001). Enhancement of bands by continuum removal is done by correcting for apparent shifts in the band minimum caused by wavelength dependent scattering, which imparts a slope to the spectrum. Removal of the continuum slope corrects the band minimum to that of the true band centre (Clark and Roush, 1984). Figure 1 shows continuum removed absorption features in the visible region, with a variation in band depth for different species.

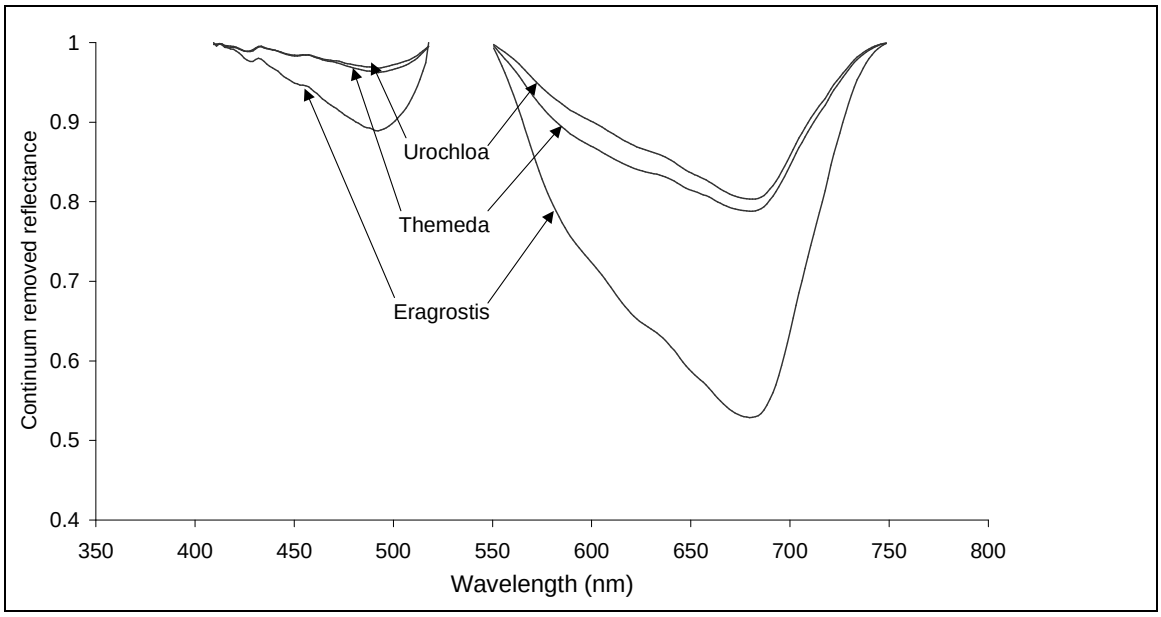

Figure 1. The absorption features ($R_{408-518}$ and $R_{550-750}$) enhanced by continuum removal for three species in the visible domain.

Continuum removal has been found useful in mapping the distribution of minerals by comparing remotely sensed absorption band shapes with those in a reference library (Clark and Roush, 1984). Efforts to apply the method in vegetation science have been made using dried plant material in the laboratory (Kokaly, 2001; Kokaly and Clark, 1999). This method has not to our knowledge been extended to estimate foliar biochemicals of grass canopies in *situ*.

Three variables were calculated from the continuum removed absorption features, *viz*. Continuum removed derivative reflectance (CRDR), Band depths (BD) and band depth ratio (BDR).

CRDR was calculated by applying the first difference transformation on the continuum removed reflectance spectrum. This transformation calculates the slope values from the reflectance and can be derived from the following equation (Dawson and Curran, 1998):

$$CRDR_{\lambda(i)} = (R'_{\lambda(j+1)} - R'_{\lambda(j)}) / \Delta_{\lambda,} \quad (2)$$

where CRDR is the first derivative reflectance at a wavelength *i* midpoint between wavebands j and j+1. $R'_{\lambda(j)}$ is the continuum removed reflectance at the waveband j, $R'_{\lambda(j+1)}$ is the reflectance at the waveband j+1 and Δ_{λ} is the difference in wavelengths between j and j+1. Band depth (BD) was calculated by subtracting the continuum – removed reflectance by 1. Formally stated:

$$BD_{(\lambda i)} = 1 - R'_{(\lambda i).} \quad (3)$$

Since remotely sensed measurements of vegetation canopies are affected by factors such as atmospheric absorptions, soil background and water, a normalisation procedure using band ratios was also done to minimise these influences (Kokaly and Clark, 1999). The normalised band depth ratio (BDR) was calculated by dividing the band depth (BD) of each channel by the band center (D_c). Formally stated:

$$BDR_{(\lambda i)} = \frac{BD_{(\lambda i)}}{D_c}. \quad (4)$$

2.4.2 Feature selection

Although the number of spectral bands used for analysis in this study had been reduced from 647 bands to 294 by concentrating on known chemical absorption features, we further reduced them using a feature selection algorithm. Forward stepwise linear regression was used to select bands that best explain biochemical variability in grass species. Stepwise regression fits a dependent data set using a linear

combination of independent data sets. Stepwise regression has been widely used to relate remotely sensed data to vegetation variables (Curran *et al.*, 2001; Kokaly and Clark, 1999; Martin and Aber, 1997; Serrano *et al.*, 2002). The maximum number of steps in the stepwise regression analysis was set at six to avoid over fitting problems. Most authors recommend 10 to 20 times as many observations as variables, otherwise the regression line estimates are very unstable and unlikely to replicate if the experiment is repeated (Serrano *et al.*, 2002; Skidmore *et al.*, 1997).

2.4.3 Testing the predictive capability of regression models

A modified bootstrap procedure was used to test the predictive capability of multiple linear regression models developed between selected absorption feature variables and biochemicals. The standard bootstrap method involves resampling of the original data in order to generate a distribution for the statistic. It simulates the sampling distribution of any statistic by treating the observed data as if it were the entire statistical population under study (Efron, 1982). On each replication, a random sample of size N is selected, with replacement from the available data (Efron and Tibshirani, 1994; McGarigal *et al.*, 2000). The statistic of interest (in this case R^2) is calculated on this bootstrapped subsample and recorded. The process is repeated for several replications in order to obtain the sampling distribution.

In this study, since we aimed at testing the predictive capability of regression models on an independent data set, we modified the bootstrap procedure by first dividing data into training and test samples (n = 72 and 24 respectively). A regression model was developed from the training data set. Next, the test data set was bootstrapped with replacement for n = 1000 times and for each iteration, a regression model from the training data set was used to predict biochemicals on the test sub sample and R^2 values recorded. The mean and standard deviation of R^2 values for the test data were calculated and recorded. A routine, developed in IDL (Interactive Data Language) was used. The method permits the calculation of standard error and confidence intervals, which indicate statistical accuracy (Efron and Tibshirani, 1994; McGarigal *et al.*, 2000).

3. RESULTS

3.1 Foliar Biochemical Concentration

The ranges of biochemical concentration were large as shown in table 2. This is mainly due to the variation in both biotic (species type) and abiotic (soil, slope, altitude) factors in the study area. Results in table 3 show that most of the foliar bio chemicals recorded are intercorrelated ($p < 0.05$) except for the correlation between nitrogen and calcium. Most of the biochemicals measured constitute the productive function in plants and are responsible for metabolic processes; hence there is a positive correlation among the biochemicals.

Table 2. Descriptive statistics of the chemical variables measured in the laboratory by species

	Mean (%)	Minimum (%)	Maximum (%)	CL (95 %)
N	0.78	0.38	2	0.055
Mg	0.21	0.06	0.41	0.017
Ca	0.44	0.14	1.03	0.031
K	0.96	0.21	2.71	0.098
P	0.18	0.04	0.48	0.018

Table 3. Intercorrelation of biochemical concentrations measured in the laboratory

	P	K	Ca	Mg
P	1.00			
K	0.74**	1.00		
Ca	0.53**	0.39**	1.00	
Mg	0.75**	0.78**	0.60**	1.00
N	0.41**	0.72**	0.26	0.50**

** Significant: $p < 0.05$

3.2 Wavelength Selection Using the Training Data Set

Stepwise linear regression was executed between biochemicals and the three methods (CRDS, BD, BDR) using the training data set (n = 72). The maximum number of selected wavelengths was set at six for each regression equation to avoid overfitting. Detailed results of the frequency of wavelengths selected by stepwise regression using the three data sets (CRDR, BD, BDR) are shown in table 4. The frequency of bands that occurs within ± 12 nm of a known chemical absorption wavelength as well as bands that have been reported in previous studies is shown. The ± 12 nm range was defined by Curran *et al.*, (2001) to indicate causal chemical absorption. The highest frequencies of bands occur in the $R_{1634 - 1786}$ and $R_{550 - 750}$ absorption features (frequency = 46). A total of 74 % of the bands selected are attributed directly (± 12 nm of the biochemical of interest) or indirectly (± 12 nm of a biochemical with which the biochemical of

interest was correlated) to known causal wavelengths (Curran *et al.*, 2001) as well as to bands reported in previous studies.

Table 4. Frequency of wavelengths selected for all dependent variables by stepwise regression on the three data sets (CRDR, BD, BDR) and their relation with known absorption wavelengths. The unattributed are wavelengths that are not within ± 12 bands of known chemical absorption as well as bands that have not been reported in other studies. The total number of bands selected in each absorption feature is also expressed as percentage of the total (in brackets).

Absorption feature centre	Wavelengths of known chemical influence (nm)	Known causal bio chemical	Reference	Frequency of bands selected (± 12 nm of known wavelength)
$\mathbf{R_{408 - 518}}$	430	Chlorophyll a	(Curran, 1989; Kumar *et al.*, 2001)	7
	460	Chlorophyll b	(Curran, 1989; Kumar *et al.*, 2001)	1
	Unattributed			3
	Total			**11 (12.4)**
$\mathbf{R_{550 - 750}}$	570	Chlorophyll + nitrogen	(Penuelas *et al.*, 1994)	7
	640	Chlorophyll b	(Curran, 1989; Kumar *et al.*, 2001)	4
	660	Chlorophyll a	(Curran, 1989; Kumar *et al.*, 2001)	3
	Red edge (700 – 750)	Chlorophyll + nitrogen	(Clevers and Buker, 1991; Curran *et al.*, 1991; Fillella and Penuelas, 1994; Horler *et al.*, 1983; Mutanga *et al.*, 2002)	6
	Unattributed			3
	Total			**23 (25.8)**
$\mathbf{R_{1116-1284}}$	1120	Lignin	(Curran, 1989; Kumar *et al.*, 2001)	2
	Unattributed			4
	Total			**6 (7)**
$\mathbf{R_{1634- 1786}}$	1690	Nitrogen	(Curran, 1989; Kumar *et al.*, 2001)	6
	1730	Nitrogen	(Curran, 1989; Kumar *et al.*, 2001)	7
	Unattributed			10
	Total			**23 (25.8)**
$\mathbf{R_{2006 - 2196}}$	2060	Nitrogen	(Curran, 1989; Kumar *et al.*, 2001)	1
	2130	Nitrogen	(Curran, 1989; Kumar *et al.*, 2001)	5
	2180	Nitrogen	(Curran, 1989; Kumar *et al.*, 2001)	8
	Unattributed			0
	Total			**14 (15.7)**
$\mathbf{R_{2222 - 2378}}$	2240	Nitrogen	[Curran, 1989 (Kumar *et al.*, 2001)	4
	2300	Nitrogen	(Curran, 1989; Kumar *et al.*, 2001)	2
	2350	Nitrogen	(Curran, 1989; Kumar *et al.*, 2001)	3
	Unattributed			3
	Total			**12 (13.5)**

3.3 Developing Regression Models From a Randomly Selected Training Data Set to Predict Foliar Biochemicals on a Test Data Set

Regression models developed from the training data set were used to predict foliar biochemicals on an independent test data set. To install confidence in the predictive capability of the regression models, a modified bootstrap procedure was adopted as explained before. Figure 4 shows an example of the predicted versus measured biochemicals using a randomly selected training and test set on CRDR data. Histograms showing the sampling distribution of the R^2 values calculated from the predicted and measured biochemicals on the test sub samples generated by the bootstrap method (CRDR data) are shown in Figure 5.The standard deviations are low for all chemicals, implying that the bootstrap method estimated with a high precision. The low standard deviations also indicate the stability of the regression models in predicting foliar biochemicals on an independent test data set. However, nitrogen yielded the highest standard deviation as compared to other biochemicals. Table 5 details the R^2 values for the training data set as well as the mean bootstrapped regression results of the accuracy with which biochemical concentration was estimated for a test data set using the three methods (CRDR, BD and BDR). The standard deviations for the test data sets are presented. Foliar biochemicals on the test data set could be predicted with mean R^2 values ranging between 0.40 and 0.70 using CRDR. Phosphorous and nitrogen were predicted with a high accuracy ($R^2 > 0.70$ using the training data set) as compared to the other biochemicals.

Table 5. Results of R^2 values for the training data set (Train) and mean of the test data sets (μ_{test}). Data was randomly divided into training and test data sets (n = 72 and 24 respectively). Next, the test data set was bootstrapped with replacement for n = 1000 times and for each iteration, a regression model from the training data set was used to predict biochemicals on a test sub sample and R^2 values recorded. The mean and standard deviation of R^2 values for the test data are presented.

Chemical	**CRDR**			**BD**			**BDR**		
	Train	μ_{test}	Stdev	Train	μ_{test}	Stdev	Train	μ_{test}	Stdev
N	0.70	0.60	0.18	0.62	0.50	0.20	0.53	0.38	0.21
K	0.64	0.53	0.17	0.72	0.60	0.16	0.56	0.33	0.18
P	0.80	0.70	0.11	0.69	0.54	0.14	0.51	0.32	0.15
Ca	0.50	0.40	0.12	0.47	0.29	0.13	0.46	0.26	0.16
Mg	0.68	0.52	0.14	0.58	0.42	0.14	0.43	0.23	0.15

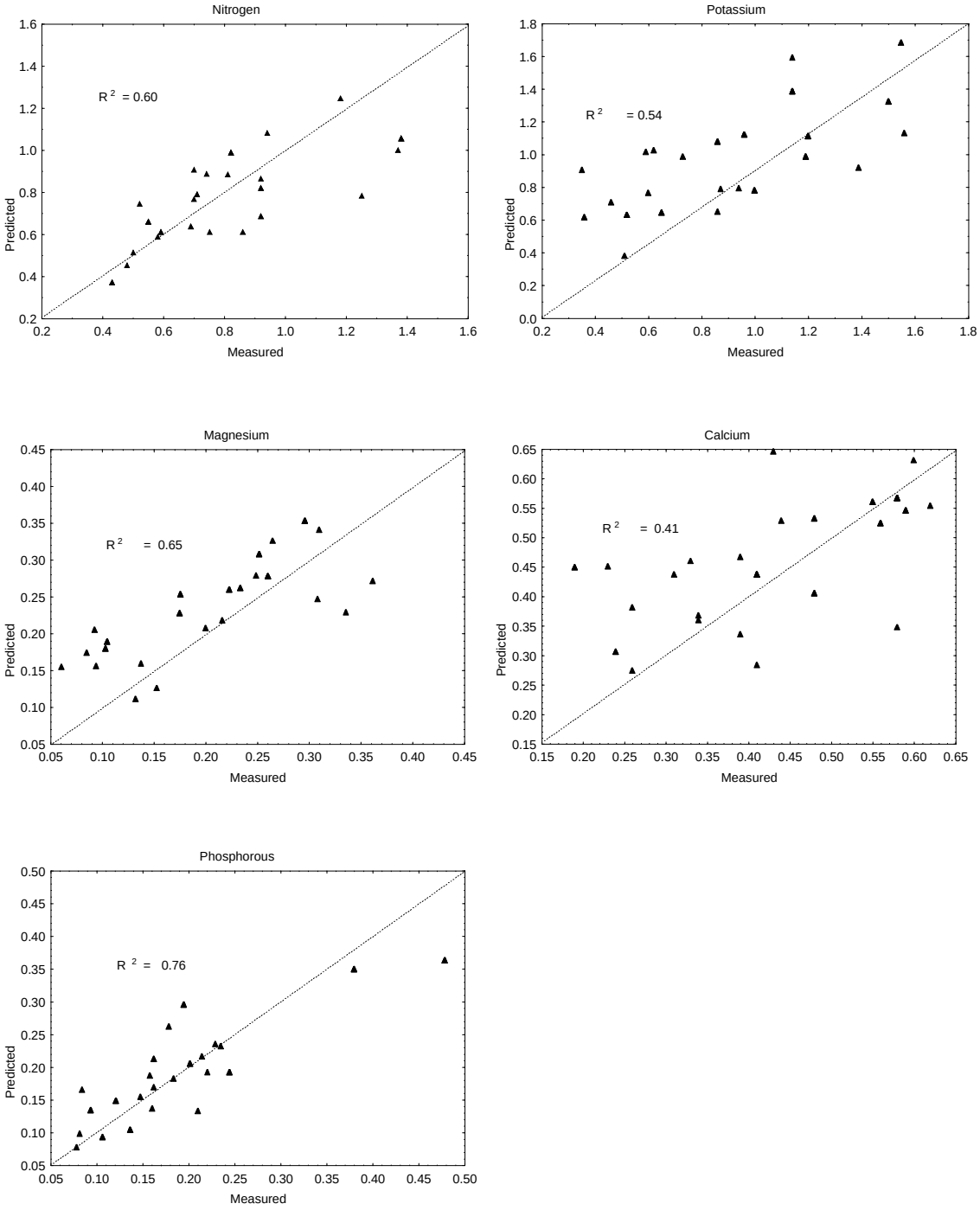

Figure 4. Measured versus predicted biochemicals using CRDR. A randomly selected test data set (n = 24) was plotted against biochemical concentration estimated using regression equations developed from the training data set (n = 72).

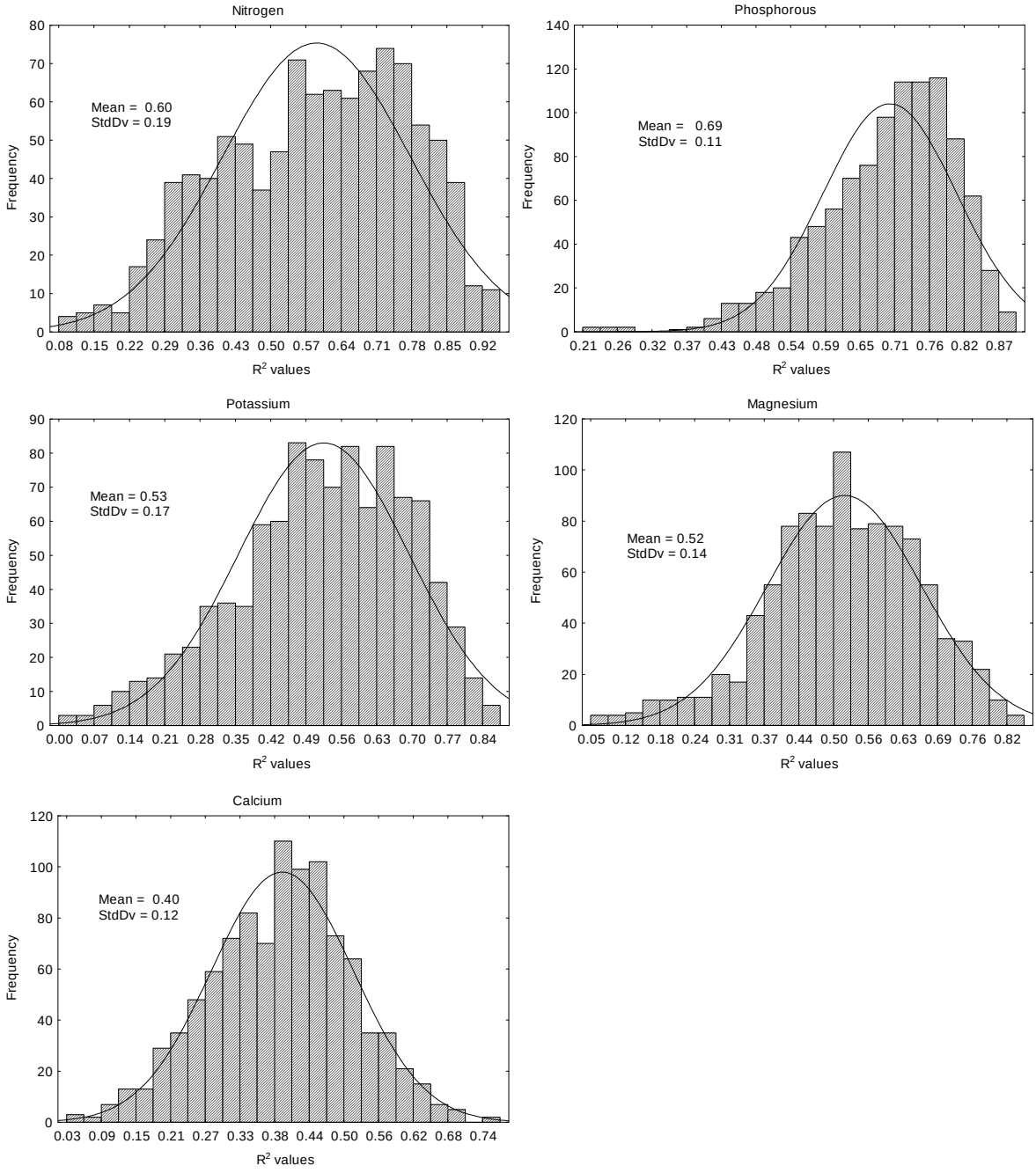

Figure 5. Histograms showing the frequency of R^2 values between the measured and predicted biochemicals on a test data set. Data was randomly divided into training and test data sets. Next, the test data set was bootstrapped with replacement for n = 1000 times and for each iteration, a regression model from the training data set was used to predict biochemicals on a test sub sample and R^2 values recorded.

4. DISCUSSION

Results from this study indicate that hyperspectral data contains information on the nutrient status of grass. Using the training data set, the methods presented in this study could explain between 43 % and 80 % of the variation in nutrient concentration of standing grass canopies measured in the field. The accuracy with which foliar nutrient concentration could be predicted on an independent data set also ranged between 23 % and 70 %. Considering that data was collected in the field under natural atmospheric and illumination conditions, this study has shown that there is potential to estimate *in situ* grass quality in rangelands using reflectance spectra.

The methods benefited from continuum removal that enhances differences in absorption strength, while normalising for absolute differences of reflectance peaks (Clark and Roush, 1984). Since this study concentrated on known absorption features, the continuum removal method enabled an increase in the variation of the band depths of individual absorption features. In a study on spectral discrimination of vegetation types in a salt marsh, Schmidt and Skidmore (2003) found out that continuum removal increases the spectral separability of vegetation types on absorption features as compared to the reflectance peaks in the near infrared. Our results are therefore consistent with previous studies. In addition the collection of data during the early dry season when most of the grass was dry reduced the effect of water on chemical absorption features, especially in the short wave infrared region. However, the results in this study are lower than those of Curran *et al.* (2001), who found higher correlations between the normalized band depth ratios and biochemicals (R^2 = 0.99 for nitrogen) using dried ground plant materials in the laboratory. This difference was to be expected since this study applied the methodology at field level where atmospheric absorptions as well as BRDF affects the signature.

There was a marked difference in the R^2 between estimated and observed biochemical concentration for the three methods derived from absorption features. The R^2 for N prediction ranged from 0.70, 0.62 and 0.53 for CRDR, BD and BDR respectively using the training data set. The same pattern was realized for the other biochemicals. Therefore, the new method, CRDR estimated biochemicals in grass with a higher accuracy than the other methods tested.

The selection of wavelengths by stepwise regression is an important step towards the development of general models for the prediction of chemicals in plants as well as serving as a guideline to select wavebands for mapping. The method presented in this study has partly solved the problem of inconsistencies found in wavelength selection from a full spectrum (Grossman *et al.*, 1996) by concentrating on a few known features of chemical absorption. However there is still need to understand particular absorption features as well as wavelengths that are important for biochemical estimation.

Wavelengths selected for biochemical estimation in the visible region (40 % of the selected wavelengths were in the visible) are linked to pigment absorption (Table 4). Several publications have shown a strong relationship between the concentration of nitrogen and the concentrations of chlorophyll *a* and *b* (Katz *et al.*, 1966; Penuelas *et al.*, 1994; Ponzoni and Goncalves, 1999). Nitrogen is related with the

protein synthesis that promotes the photosynthetic process. Therefore, nitrogen deficiency disturbs the metabolic function of the chlorophyll, which is the photosynthetic element responsible for the absorption of electromagnetic energy at specific wavelengths in the visible region (Ponzoni and Goncalves, 1999). Since chlorophyll largely determines spectral reflectance in the visible, a strong relationship between visible absorption bands and nitrogen concentration is also expected.

This study has also shown a strong intercorrelation among biochemicals themselves, particularly NPK (Table 3). Phosphorous is fundamental for tissue composition as well as being one of the components of the nucleic acids and enzymes. Potassium is also important for activating enzymes responsible for the carbohydrates metabolism as well as in the apical dominance (Ponzoni and Goncalves, 1999). These elements are therefore responsible for both the photosynthetic process and tissue composition of plants, hence related with the visible absorption bands (Salisbury and Ross, 1985).

Most wavelengths selected in the SWIR (66% of selected wavelengths in the short wave infrared) are ± 12 nm of the known protein absorption bands, specifically bonds including nitrogen. The intercorrelation of chemicals (Table 3) explains the selection of most bands close to regions of nitrogen absorption. The selected wavelengths (Table 4) are linked to the absorption of electromagnetic radiation by biochemicals that originates from energy transition of the molecular vibration (rotation, bending and stretching) of the C-H, N-H, O-H, C-N and C-C bonds in plant tissues (Elvidge, 1990). The chemical constituents of the plant tissue determine the nature and number of bonds present. Therefore, the wavelengths and the amount of energy reflected from the plant are partly a function of the chemical composition of that plant material (Foley *et al.*, 1998). Overall, the two chlorophyll absorption features and the nitrogen absorption feature in the SWIR ($R_{1634 - 1735}$) accounts for most wavebands selected in this study.

5. CONCLUSION

This study has applied an empirical method to estimate grass quality at field level. Normalized band depths as well as derivatives calculated from continuum-removed reflectance spectra, were used in stepwise regression using six major absorption bands in the visible and the short wave infrared. The following conclusions can be drawn from this study:

(i) Stepwise regression on normalized bands calculated from continuum-removed reflectance spectra could explain the variation of *in situ* grass quality with an accuracy ranging between 43 % and 80 %.

(ii) The new method, CRDR performed better than any other method tested in estimating grass quality (R^2 of 0.70, 0.80, 0.64, 0.50 and 0.68 for N, P, K, Ca and Mg, respectively) using the training data set

(iii) From the three absorption feature based methods tested, the accuracy with which biochemical concentration was estimated for a test data set ranged from an R^2 of 0.23 to an R^2 of 0.70

(iv) The highest frequencies of bands selected by stepwise regression occur in the $R_{1634 - 1786}$ and $R_{550 - 750}$ absorption features (frequency = 46). This serves as a guideline for the selection of important absorption features for mapping grass quality in tropical rangelands.

Overall, the successful use of absorption features for estimating grass quality at field level is an important step towards the remote sensing and mapping of rangelands. These results have important applications not only in animal ecology, but also in agriculture and in understanding biogeochemical cycles.

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