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# USING INFRARED SPECTROSCOPY FOR DETECTION OF CHANGE IN SOIL PROPERTIES IN SELECTED LANDUSES IN MT. MARSABIT ECOSYSTEM, NORTHERN KENYA

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**Abstract**

The conversion of forest to smallholder cropland is one of the most common type of land use change in the tropics. Forest margin cultivators respond to deteriorating soil fertility and declining crop yield by cultivation on the forest margins in an attempt to create "*new*" fertile cropland. A critical constraint to managing soils in sub Saharan Africa is poor targeting of soil management interventions. This is partly due to lack of diagnostic tools for screening soil condition that would lead to a robust and repeatable spatially explicit case definition of poor soil condition. The objectives of this study was to evaluate the ability of near infrared spectroscopy to detect changes in soil properties.
The effects of forest conversion and subsequent cultivation on carbon stocks and soil properties were monitored in demarcated land use types (forest, cropped and pasture land) along transects within the Mt. Marsabit ecosystem in northern Kenya. Total carbon ranged between 1.99 – 17.74 $gkg^{-1}$ in the forest, 1.17 – 3.08 $gkg^{-1}$cropped 1.62 – 4.77 $gkg^{-1}$ pasture land use systems. The soil properties total carbon, total nitrogen, pH, exchangeable magnesium, calcium and CEC were significantly lower ($P \leq 0.001$) in cropped and pasture compared to forest and their variations were successfully predicted ($r^2 > 0.76$) using near infra red spectroscopy (NIRS) is high prediction accuracy. The spectral separability of the three land use systems offers promise for an approach that utilizes NIRS for monitoring changes in soil properties. The study concludes that reflectance spectroscopy is rapid and offers the possibility for major efficiency and cost saving, permitting spectral case definition to define poor or degraded soils, leading to better targeting of management interventions.

Key words: Spectral detection, reflectance, soil properties, land use systems

## Introduction

In Africa, forests and rangelands are under threat from human population pressures and changes in land use (FAO, 1990). Projected population growth in the tropics will require the expansion of agricultural production. This can be achieved by either increasing yield per unit area in existing agricultural land through high input farming systems or taking more land for production through conversion of forests, grasslands and wetlands. The conversion of tropical forest to smallholder cropland is one of the most common type of land use change in Africa (Moss, 1993). Agricultural expansion in the tropics, through deforestation has major environmental implications with potential causal links to degradation of the natural resource base. At the global level, this invariably leads to loss of biological diversity, raises the specter of climate change, and disrupts hydrological cycles (Young, 1997). At the local scale it leads to soil fertility decline, crop production loses, and decline in water quality from increased sediment loads arising from runoff and soil erosion. (Sanchez, 1976; Nair, 1990; Moss, 1993).

Mount Marsabit and its environs is a unique ecological system in Eastern Africa with the most developed and extensive upland forest on an extinct volcano within an arid setting. This upland forest has over thousands of years developed a distinct plant association endemic to this area. It is the only source of water for the surrounding desert region (National Development Plan, 2002-2008). Currently, the Marsabit Mountain forest occupies an area of 15 $km^2$ (About 15,280 ha) but it is disappearing at the rate of 1.6 ha per year. The national closed-canopy forest cover now stands at 2-3% (FHI, 2001). Population increase and lack of adequate farm lands have led to many people turning to converting forests to agricultural lands for their livelihoods. Marsabit forest ecosystem is threatened by many factors such as increasing demand for firewood and building materials, encroachment as a result of expansion of the Marsabit town population, overgrazing, and forest fires. These activities have led to forest degradation. There is also increased conversion of the forested areas into farmlands outside and within the forest reserve. Widespread deforestation for fuel wood and other domestic uses has accentuated the impact of harsh dry environments (Boahene, 1998).

The conventional assessment methods to determine soil degradation include plot level, laboratory or experiment base. These methods are expensive, time consuming and very specific. A number of different tests are typically required to provide case-specific diagnoses. The results obtained at one site cannot be replicated at another site with relevant outcomes, owing to high spatial and temporal variation in environmental and decision situations. Large numbers of samples are often required to detect significant changes. This precludes the use of most soil testing procedures for monitoring, evaluation, and impact assessment of land management (Shepherd et al 2007).

There is no scientific consensus on the definitions of appropriate endpoints or indicators for assessing the impacts of land use systems on soil productivity decline at the landscape or farm level (Shepherd and Walsh, 2000). The assessment of diverse effects of land use and land use change on soil productivity requires the integration of physical, chemical and biological attributes of the soil. Methods that can provide rapid and integrated assessments of soil productivity are urgently needed. These methods should be sensitive to the physical and chemical attributes of soil, as affected by land use and land management factors at the plot and landscape level. Developments in laboratory and field based reflectance spectrometry present a unique capability for rapid, cheap, integrated assessments and routine monitoring of soil productivity status (Janik *et al.*, 1998; Shepherd and Walsh, 2000; Chang *et al.*, 2001; Confalonieri, 2001). However, there has been little focus on the application of reflectance spectrometry in the assessment of different soil functions and their response to fertility management. The purpose of this study was to demonstrate the ability of NIRS to evaluate the use of near infrared spectroscopy for non-destructive characterization and prediction of management sensitive soil properties under different land use systems.

## MATERIALS AND METHODS

### Study area

Mount Marsabit ecosystem is located in northern Kenya (Figure 1). The district lies between latitude $01^0$ 15' North and $04^0$ 27' North and longitude $36^0$ 03' East and $38^0$ 59' East.

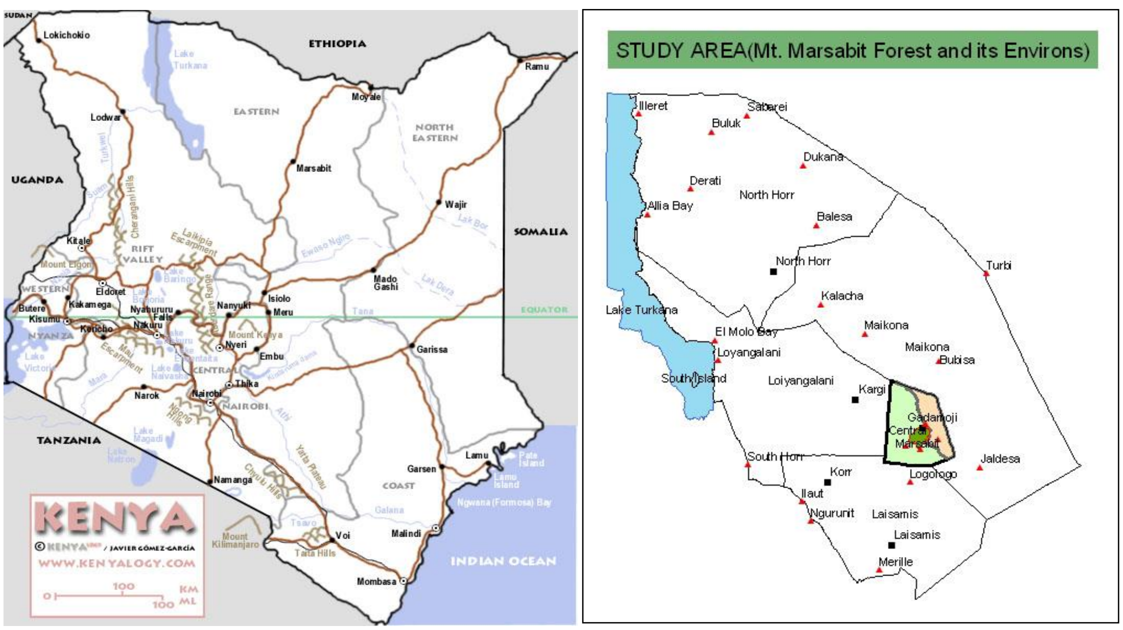



**Figure 1:** Mt Marsabit Forest and its environs

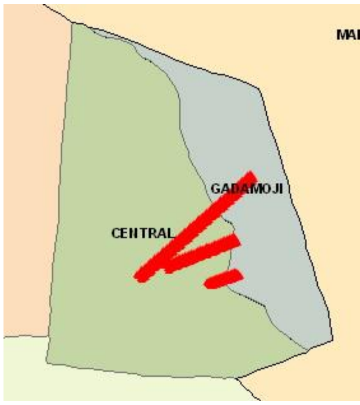



**Figure 1b: Sampling transects across the three land use systems**

The district receives between 200 mm to 1,000 mm of rainfall per annum for the lowest to the highest elevation respectively. The rainfall displays both temporal and spatial variation and is bimodal. The district occupies the driest region in the country. Low rainfall combined with high temperature result in high evapo-transpiration rates that exceed annual precipitation leading to a marked moisture deficiency (National Development Plan, 2002-2008). The area around Mt. Marsabit can be classified into 4 different agro-climatic zones. These are Sub-humid, Semi-arid, Arid, and Very arid zones. The soils are deep, well drained, volcanic, high in organic matter, reddish - brown clay to clay loam (FHI, 2001). The major land use is agriculture mostly pastoralism with patches of crop production.

**Soil sampling and analysis**

Assessment of carbon stocks was carried out in different vegetation or land-use systems. Stratification to obtain a clear, operational definition of the unit of analysis was done. cluster survey design as described by Shepherd *et al*. (2002). A cluster comprised of 13 plots measuring 30 by 30 m each systematically laid out. One cluster was randomly located in each land use within a transect in a quadrat in transects A, B and C (figure 1b). All plots were geo-referenced at their center-points (15 m) using a survey grade differential global positioning system (GPS). Soils were collected in mid January to February 2005, just before the onset of long rains. Soil and litter samples were recovered from a 900 $m^2$ quadrat. Using an auger, soil samples were collected at two depths 0-20 and 20-50 cm, where soil depth allowed. Soil samples were taken at the 5, 15, and 25 m positions of the center line of the plot and in direction of the dominant slope gradient. Soil profile pits upto 1.5 m depths were dug in three plots within a cluster. Soils from pit walls were collected at 10 cm intervals up to a depth of 150 cm using core rings (5 cm diameter and 5 cm height) to assess carbon changes with depth. All samples were air-dried, crushed and passed through a 2-mm sieve for spectral and chemical analyses. A portion of each crushed sample was further passed through a 0.5-mm sieve for total carbon and total nitrogen determination.

### Near Infrared Reflectance Spectroscopy measurements

The air dried soil passed through a 2-mm sieve was packed in 12 mm deep and 55 mm diameter Duran Petri dishes. Reflectance spectra were recorded for each soil sample using a FieldSpec$^{TM}$ FR spectroradiometer (Analytical Spectral Devices Inc., 1997) at wavelengths from 0.35 µm to 2.5 µm with a spectral sampling interval of 0.01µm. The samples were scanned through the bottom of the Petri dishes using a high intensity source probe (Analytical Spectral Devices Inc., 1997). The probe illuminated the sample (4.5 W halogen lamp WelchAllyn, Skaneatles Falls, NY) giving a correlated colour temperature of 3000 K. This also collected the reflected light from 3.5 cm diameter sapphire window through a fibre optic cable. Reflectance spectra were recorded at two positions, successively rotating the sample dish through 90$^{o}$ between readings to sample within dish variation. The average of 25 spectra (manufacturers default value) was recorded using calibrated spectralon (Labsphere®, Sutton, NH) placed in a glass Petri dish as a reference. Reflectance readings of each wavelength band were expressed relative to the average of the white reference readings.

### Near Infrared Reflectance Spectroscopy

Spectroscopic transformation (CAMO Inc., 1998) was applied to convert spectral reflectance to absorbance (logarithmic transformation of the inverse of reflectance). Another data treatment applied was the first derivative processing (differentiation with second order polynomial smoothing with a window width of 0.02 µm) using a Savitzky-Golay filter as described by Fearn (2000). Derivative transformations minimize variation among samples caused by variations in grinding and optical set-up (Marten and Naes, 1989).

In this study, a calibration set of 74 samples which made a third of the total number of augured samples (222) were selected. This calibration set was selected based on the samples contributing most to the different spectra and the shortest squared Euclidean distance from the centre sample in principle component space. Principle component analysis was implemented in Unscrambler version 7.5 (CAMO Inc, 1998). Individual soil variables were calibrated against 214 (0.36-2.49 µm) reflectance bands using Partial Least Squares (PLS) regression (Martens *et al*, 2000; Shepherd *et al* 2007). Cross validation was applied to determine the optimum number of factors (latent variables) needed to describe all the variation in the data to guard against over fitting. Cross validation was done by successively removing sub-sets of calibration samples from the model estimation and using them as temporary, local test samples (Martens *et al*, 2000; Shepherd *et al* 2007). In essence, sample one in the calibration set was deleted and calibration performed on the rest of the samples. The procedure was repeated by deleting sample two until all samples had been deleted from the model at least once (Naes *et al*., 2002). The calibrations were tested by predicting the respective soil properties on the validation data set comprising the remaining one third of 74 soil samples. The coefficient of determination ($r^2$), root mean standard error of prediction (RMSE) and bias were used to evaluate the prediction ability of the near infrared PLS technique. The analyses were performed using the software Unscrambler version 7.5 (CAMO Inc, 1998).

## Results and Discussion

### Chemical and physical soil properties

Table 1 shows the chemical and physical soil properties measured in the three land use systems. The data shows that soils under forest, cropped and pasture differed significantly in a number of chemical attributes. The mean C and N contents were significantly different ($p \leq 0.001$) in soils under forest compared to those in cropped and pasture. Carbon content declined by 32.1% and 42.8% in cropped and pasture land, respectively, relative to the forest soils. The nitrogen contents showed a similar trend and declined by 53.6% and 43.2% in cropped and pasture land as compared to the forest soils.

The trends suggest that N losses from converted sites are higher than C losses. This may account for the high C: N ratio in the pastureland and forest relative to the cropped lands and could be due to the forest's higher root biomass. Janik *et al.* (1995) noted that high C:N ratio plant residues produce a strong demand for N by heterotrophic soil microbes leaving less N available for nitrification, leading to low N supply in the soil. Soil organic matter having a C: N ratio of less than 30 is easily mineralized and releases soluble inorganic N whereas SOM having a C: N ratio greater than 30 is more resistant to mineralization (Juo and Franzluebbers, 2003).

Exchangeable Ca and Mg were significantly ($p \leq 0.001$) higher in forest compared to pasture and cropped areas. This could be due to a high rate of removal through leaching and uptake by crops compared to trees. Janik *et al.* (1995) attributed decline in exchangeable Ca and Mg to leaching and crop uptake and removal.

Exchangeable potassium (K) was not significantly different ($p \leq 0.402$) among the land use systems (LUS) probably due to its luxury consumption and leaching as weathering advances. The CEC was lower in cropped and pasture lands compared to forest. Converting forests to crop production or grasslands depletes SOM and hence soil carbon content which may also result in decrease in base cation retention (Sanchez, 1976; Mann, 1986; Juo and Franzluebbers, 2003). The high amounts of P in the cropped lands could be due to additions of phosphorus rich manure by farmers compared to no addition in forests and pastureland. The soil texture ranged from loam in forest to clay in cropped and pastureland. This is due to the topography such that forest is undulating compared to the cropped and pasturelands eluviations and erosion could be the reason for higher sand and silt in the forest compared to cultivated and range lands.

Decline in SOM and other soil attributes namely total N, exchangeable Ca, CEC and particle size distribution, and increase of others namely pH and Mg in the study area have resulted in decline in agricultural productivity. The effects of forest conversion and subsequent cultivation on soil properties is such that there is a rapid decline on the soil properties as opposed to the forest system. Forest is a closed system so everything recycle within. Cropland and pastureland are open systems where nutrients are mined through crop removal and grazing, respectively, unlike the forest.

**Table 1**. Soil chemical and physical properties in the three land use types

| Soil property | Forest | | | | Cropland | | | | Pastureland | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Range | Mean | SE | n | Range | Mean | SE | n | Range | Mean | SE | n |
| pH | 5.5 – 7.6 | 6.7 | 0.01 | 32 | 6.7 – 8.2 | 7.3 | 0.09 | 23 | 6.9 – 7.5 | 7.2 | 0.03 | 19 |
| Exch. Ca, cmol/kg | 3.25 – 16.5 | 11.1 | 0.64 | 32 | 5 – 10.25 | 7.07 | 0.31 | 23 | 5.38 – 12.13 | 8.92 | 0.46 | 19 |
| Exch. K cmol/kg | 2.5 - 21 | 11.58 | 1.02 | 32 | 5 – 24.5 | 11.46 | 0.8 | 23 | 5 - 15 | 9.26 | 0.53 | 19 |
| CEC cmol/kg | 17.6 – 47.9 | 36.89 | 1.26 | 32 | 23.7 – 38.6 | 29.18 | 0.78 | 23 | 23.9 – 35.5 | 29.96 | 0.73 | 19 |
| Exch. Mg, cmol/kg | 3.75 – 10.63 | 7.43 | 0.26 | 32 | 5.83 – 12.5 | 8.2 | 0.38 | 23 | 6.25 – 12.5 | 9.49 | 0.46 | 19 |
| Organic Carbon g/kg | 1.99 – 17.74 | 6.54 | 0.66 | 32 | 1.17 – 3.08 | 2.11 | 0.12 | 23 | 1.62 – 4.77 | 2.79 | 0.23 | 19 |
| Total Nitrogen g/kg | 0.55 – 2.12 | 1.25 | 0.08 | 32 | 0.28 – 1.02 | 0.67 | 0.05 | 23 | 0.28 – 0.86 | 0.54 | 0.03 | 19 |
| Ext. P mg/kg | 5.5 – 52.5 | 21.83 | 2.18 | 32 | 5 - 350 | 91.85 | 17.4 | 23 | 2.5 - 60 | 22.64 | 3.97 | 19 |
| Clay g/kg | 2 - 50 | 26.5 | 2.21 | 22 | 31 - 58 | 46.4 | 1.6 | 23 | 32 - 58 | 44.4 | 1.7 | 18 |
| Silt g/kg | 23 - 66 | 36.8 | 1.84 | 22 | 19 - 43 | 28.7 | 1.4 | 23 | 19 - 41 | 31.2 | 1.57 | 18 |
| Sand g/kg | 26 - 54 | 36.7 | 1.62 | 22 | 22 - 26 | 24.9 | 0.28 | 23 | 21 - 31 | 24.4 | 0.56 | 18 |

**Characterization and prediction of management-sensitive soil properties using NIRS**

Mean relative reflectance varied among the three LUS (Figure 2). However, the mean soil spectral reflectance from the three LUS exhibited similar pattern indicating similar mineralogy. Relative reflectance averaged across the entire spectrum (albedo) of all the soils ranged from 0.025 to 0.28.

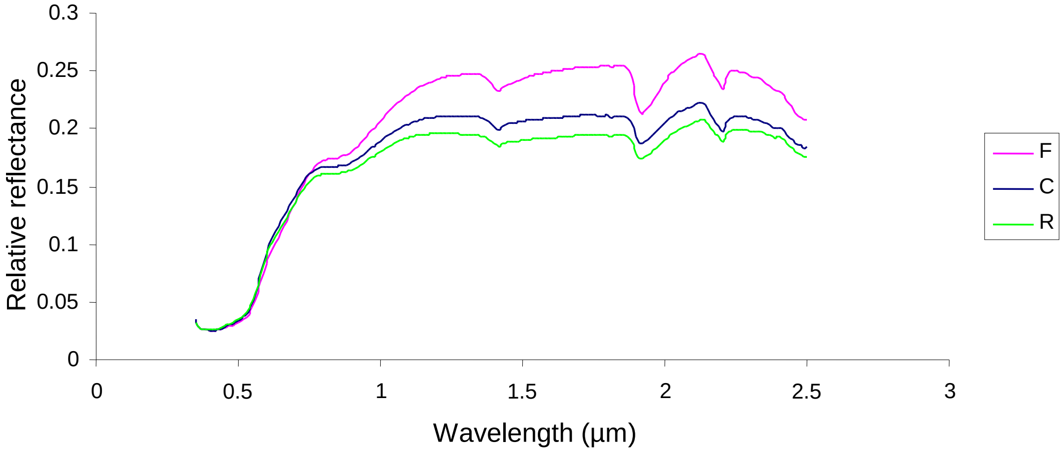
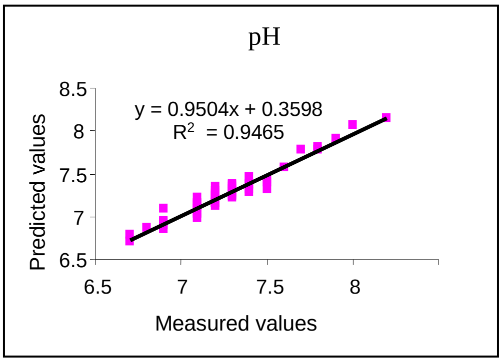



**Figure 2:** Near Infrared Reflectance Spectroscopy of forest (F), cropland (C) and pastureland (R) soil samples.

Spectral reflectance patterns among the three LUS were low in the visible region and absorption bands at 1.4, 1.9, and 2.2 µm wavelength region. Other researchers (Ben-Dor *et al*., 1999; Shepherd and Walsh, 2002) have also reported similar results. Differences in albedo are related to soil organic matter contents (Baumgardner *et al.*, 1985; Ben-Dor *et al*., 1999) with absorption features occurring at wavelengths 1.4, 1.9, and 2.2 µm. These absorption features were associated with clay minerals, the hydroxyl (OH) ions occur at 1.4 and 1.9µm and the clay lattice (OH) ions at 1.4 and 2.2 µm (Hurrt, 2002). Variation in the visible range and at the 0.9 µm are commonly associated with $Fe^{2+}$ and $Fe^{3+}$ (Hurrt, 2002), but could also be influenced by organic matter contents (Ben-Dor *et al*., 1999).

a,

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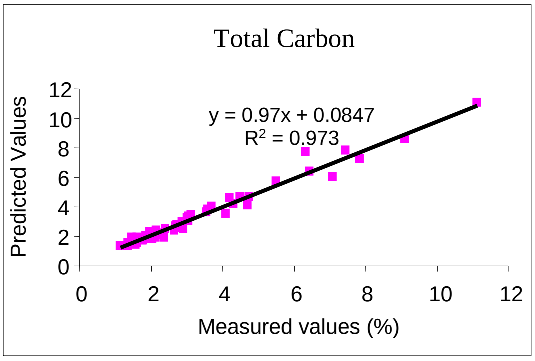

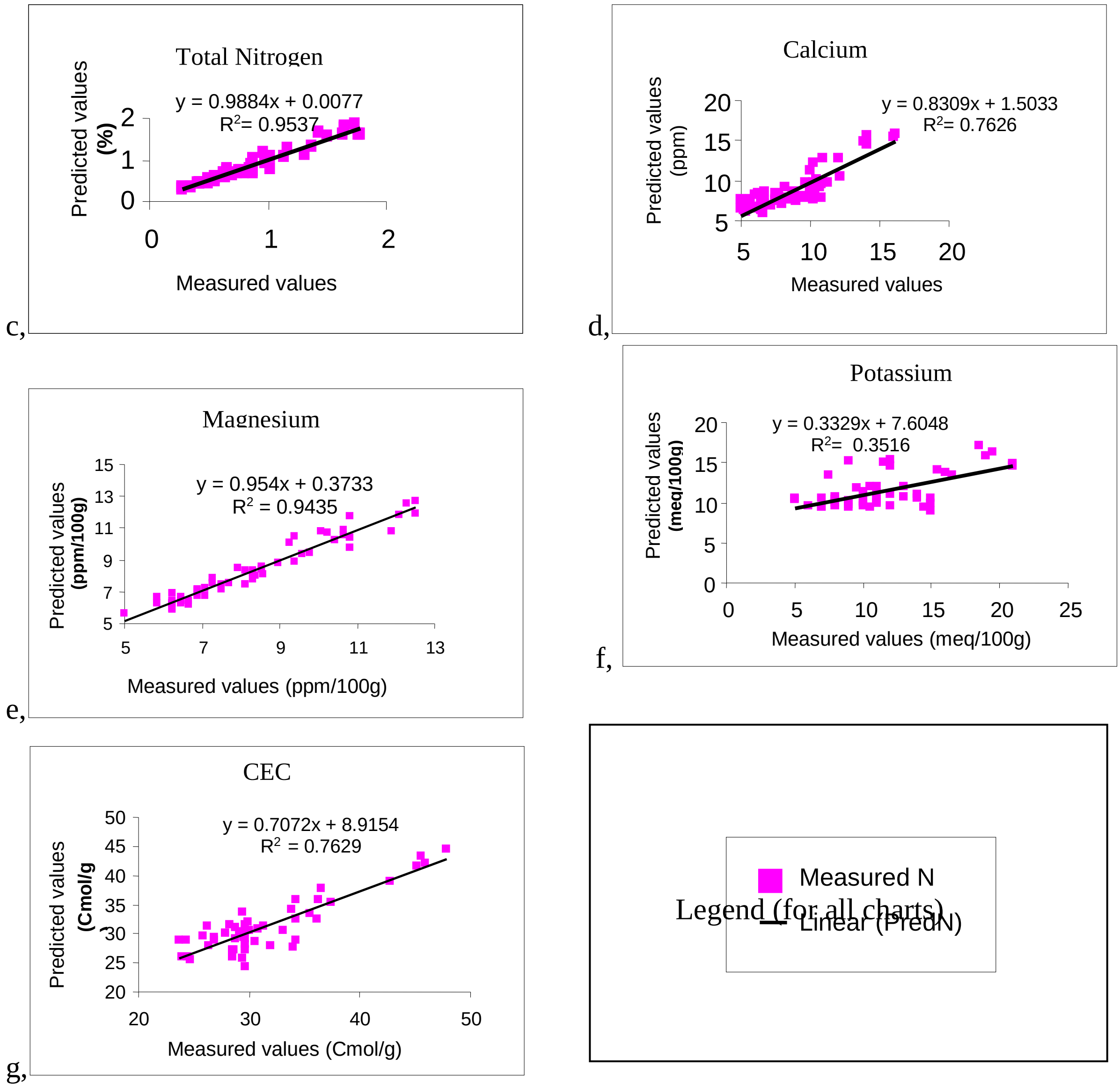


**Figure 3**: Regression of soil properties measured by standard laboratory procedures and predicted by NIRS – PLS techniques.

**NIRS Prediction of Soil Properties using Partial Least Squares Regression**

Figure 3 shows regression of soil properties measured by standard laboratory procedures and predicted by NIRS - PLS technique. It can be observed that major soil characteristics such as carbon, nitrogen, pH, exchangeable magnesium and calcium, and CEC were reliably predicted ($r^2 > 0.76$) by NIRS-PLS. Generally, the cross validation models with high regression ($r^2$) values such as those obtained with N, CEC and exchangeable Ca also yielded large validation $r^2$ values ($r^2 > 0.76$). The fact that these properties were highly correlated with carbon ($r^2 = 0.97$), may explain this high prediction accuracy attained using the validation data set. However, pH ($r^2 = 0.95$) and exchangeable Mg ($r^2 = 0.94$) were more accurately predicted by NIRS-PLS than would be expected based on their correlations with carbon. Correlation coefficients of extractable K was very low ($r^2 = 0.35$).

The accuracy of prediction for total carbon, total nitrogen, exchangeable calcium and CEC are comparable to those already reported by Chang *et al.* (2001) and Shepherd and Walsh (2002). For instance, for 62 validation samples of total carbon ranging between 9 – 73 $gkg^{-1}$, $r^2$ was 0.91, the bias was -0.7 $gkg^{-1}$ with RMSE of 3.77 $gkg^{-1}$. Shepherd and Walsh (2002) reported $r^2$ of 0.8, bias of -0.1 $gkg^{-1}$ and RMSE of 3.1 $gkg^{-1}$ for total carbon values between 2.3 -55 for a sample size of 337 soils. Similarly, predicted and measured values for total N, $r^2$ = 0.9; bias = -0.01 $gkg^{-1}$; RMSE = 0.49 $gkg^{-1}$. Confalonieri *et al.* (2001) reported that NIRS can be used to determine soil nitrogen and carbon content accurately.

The NIRS gave good estimates of the management induced changes in soil properties namely C, pH, N, CEC, exchangeable Ca and Mg, and particle size distribution as a result of land conversions. This technique offers great potential for estimating and monitoring variations in soil constituents under different land use systems. The main merits of NIRS are its repeatability and speed compared with conventional soil analyses. NIRS is reputed to give better precision and accuracy than the actual reference measurement (Naes *et al*., 2002), particularly when the error in the reference measurement is large.

## Conclusions

NIRS was sensitive to changes in soil properties caused by forest conversion and cultivation and gave good estimates of management induced changes in soil properties including total C and total N, CEC, exchangeable Ca and Mg, and particle size distribution. Significantly, these are primary soil constituents for which a theoretical basis for reliable NIRS prediction exists. NIRS spectroscopy offers great potential for estimating and monitoring variations in these constituents under different land use land management scenarios. Hence an important future direction for research is to develop a spectral library of referent or benchmark sites at a landscape scale. These benchmarks should be sites that are representative of undisturbed native vegetation types from which current managed systems are derived. These libraries will provide a spectral baseline for routinely monitoring changes in attributes of soil functional capacity in cultivated and grazing systems relative to undisturbed sites for precise management of agricultural productivity.

The spectral seperability of managed systems relative to an undisturbed benchmark therefore offers a new research vision: a vision that anticipates soil fertility decline stemming from inappropriate land use and land management practices and offers integrated strategies for timely ecologically sound intervention approaches based on a clear understanding of soil fertility decline pathways relative to known reference conditions. Future studies should explore approaches that combine Discriminant analysis and strategic spectral libraries of pre-agriculture (benchmark) soil conditions with information on physical, chemical and biological properties. These spectral libraries will form the basis of multivariate classification models for developing robust benchmark similarity indices at the landscape level. In particular these methods will accelerate the development of risk-based approaches that explicitly account for site history and land use management.

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