Soil carbon estimation from *eucalyptus grandis* using canopy spectra

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Abstract

Mapping soil fertility parameters, such as soil carbon (C), is fundamentally important for forest management and research related to forest growth and climate change. This study seeks to establish the link between Eucalyptus grandis canopy spectra and soil carbon using raw and continuum-removed spectra. Canopy-level spectra were collected using a hand-held 350-2500nm spectroradiometer and soil samples obtained at depths from 0-1.2m and analysed for carbon content. Partial least squares (PLS) selection was used to selected optimal bands for soil carbon assessment and further bootstrapped to select 35 Variable Importance in Projection (VIP) parameters, based on correlation (r) and standard error (SE). Results indicated that continuum-removed spectra and soil C yielded stronger significant correlations, when compared to soil C and raw spectra. The predictive models developed for future soil C estimation showed that continuum-removed spectra exhibited improved adjusted R^2 values in both instances, i.e., when using all significant bands and the most significant 35 VIP bands. The results indicate a distinct potential for forest managers to monitor the status of soil C in commercial forestry compartments using canopy-level spectra and determine how much fertilizer is required to optimize tree growth.

Keywords: Soil carbon, Canopy spectra

Introduction

Soil represents a fundamental resource when it comes to the provision of a range of even general ecological functions, such as fibre production, food security, biodiversity, and environmental services (Biazin *et al.* 2012). Soil fertility refers to an adequate supply of the micro and macro nutrients which promote and support long term sustainable productivity of the soil (Adams *et al.* 1998). Soil fertility-related chemical parameters, such as carbon (C), nitrogen, soil organic matter, soil salinity content, soil pH, calcium, magnesium, sodium, potassium, and phosphorus contents, previously have been assessed using conventional field-based methods (Viscarra Rossel *et al.* 2006). The major disadvantages of field-based methods are the generation of toxic wastes, e.g., chromate oxidation (Walkley and Black, 1934), which require careful and proper disposal, combustion products (Allison et al, 1965), their expensive and time-consuming nature (Watson *et al.* 2000, McCarty *et al.* 2002). Remote sensing are seen as straightforward, inexpensive, robust, and non-invasive, while such approaches also did not utilise environmentally harmful extractants (Viscarra Rossel *et al.* 2006, Koruyan *et al.* 2012).

Soil C is a key attribute of soil quality and influences a variety of biological, chemical, and physical properties of soils (Carter 2002). Soil carbon also serves as a primary source of energy and nutrients for many soil organisms (Aïchi *et al.* 2009) and is inconstant in both space and time (Batchily *et al.* 2003). Timely and continuous assessment of soil C requires state of the art technologies that can quantify the relationships between leaf nutrient concentrations and soil nutrients (He *et al.* 2014). Spectroscopy datasets, including laboratory based and air borne or space borne imaging spectroscopy, have been used in the past to assess soil C content (Brunet *et al.* 2007, Gomez *et al.* 2008).

Aïchi *et al.* (2009) attempted to develop a regional predictive model of soil organic carbon (SOC) content, based on laboratory measurements of spectra within the visible and near-infrared spectral ranges (400-2500nm). The authors reported relatively high coefficients of determination for both calibration (R^2 =0.91, RMSE = 0.36 %) and validation (R^2 = 0.83, RMSE = 0.46 %) datasets. The main conclusion stemming from this study was that the combination of spectral measurements and the partial least square regression (PLS) approach was fundamentally important in the rapid assessments of SOC, and can therefore be used for spatial prediction of soil properties over large areas.

Soil is a more heterogeneous material than vegetation, which eventually results in greater difficulties in applying quantitative analyses to hyperspectral remote sensing soil data. Ben-Dor *et al*. (1997), Bartholomeus *et al*. (2008), and Summers *et al*. (2011) have shown that the visible, near-infrared, and shortwave infrared (VNIR-SWIR, 400-2500 nm) regions are useful for assessing soil properties, if careful laboratory conditions and spectral manipulation techniques are employed. They furthermore showed that for several soil properties, a large number of spectral channels are not always required to accurately predict the property in question (number of channels required ranged between 15 and 300). The successes of laboratory spectroscopy for assessing various soil chemical characteristics led scientists to believe that correct optimisation of laboratory approaches could be extended robustly over large areas (Farifteh *et al.* 2006) using airborne imaging spectroscopy platforms (Ladoni *et al.* 2010). Such sensors are known to produce near-laboratory characteristics due to high signal-to-noise ratio (e.g. AVIRIS next generation), thus enabling the extension from laboratory to field environments (Hamlin *et al.* 2010). Stevens *et al.* (2010) managed to relate surface SOC content of bare croplands using 3 different multivariate calibration techniques *viz.* partial least square regression (PLSR), penalized-spline signal regression (PSR), and support vector machine regression (SVMR) using the airborne hyperspectral sensor 160 on-board of a CASA 212-200 aircraft. The authors reported encouraging results for both calibration and validation datasets with acceptable root mean square error values (RMSE). The Hymap sensor was shown to exhibit better model fits (R^2 = 0.9) between predicted and observed values for the mapping of SOC content of agricultural fields, when compared to CASI data, which yielded R^2 values ranging from 0.7-0.84 (Uno *et al.* 2005, Selige *et al.* 2006, Stevens *et al.* 2008). Many reported soil carbon assessments studies using imaging spectroscopy datasets were conducted in bare soil environments and not in vegetated areas (Uno *et al.* 2005, Selige *et al.* 2006). An alternative approach, i.e., the assessment of soil carbon under vegetated areas, can result in an innovative and operational approach, given the land management scenarios which require remedial action to combat environmental degradation, promote commercial forestry farming, and improve the aestheticity of the environment (Aulakh 2010, Allen *et al.* 2011).

The premise of using canopy-level spectroscopy to assess soil fertility parameters is based on the assumed direct relationships between canopy chemical bioassays and soil nutrients for vegetated areas. Logically, a scientific hypothesis behind such a premise is that vegetation health is a function of the nutrient and water content contained within the soil (De Boeck *et al.* 2007). The research question that this study aims to answer is: Does a relationship exist between canopy-level, foliar spectra of *Eucalyptus grandis* and soil carbon content in the Highlands estate in Richmond area of KwaZulu-Natal, South Africa? The spectroscopy studies which assess foliar chemical constituents as proxies to the soil fertility status in South Africa in short-rotation, highly productive commercial forestry sites are severely lacking. This study seeks to establish the link between soil carbon and leaf spectra obtained from a hand-held spectroradiometer at canopy level. Such efforts are envisaged to enable rapid and extensive assessment of soil health using vegetation reflectance metrics as proxies, before deteriorating soil-foliage signs are visible to the naked eye.

Material and Methods

Study area

The study was conducted in the Highlands estate in Richmond area, KwaZulu-Natal, South Africa (Figure 1), which experiences cold dry winters and warm wet summers. The mean annual rainfall ranges from 746-1100mm, while temperatures vary between a high of 25°C to below 10°C (Schulze, 1997). The dominant soil forms are Inanda and Mogwa, with Hutton being the subdominant soil form. Huttons are characterized by a topsoil (0.4-0.5m) on a red, apedal, clay loam subsoil (>1m). A large number of *Eucalyptus grandis* plantations in the area are located on this Hutton soil form. The topography of the Richmond area is flat with undulating hills and is classified as being low mountains.

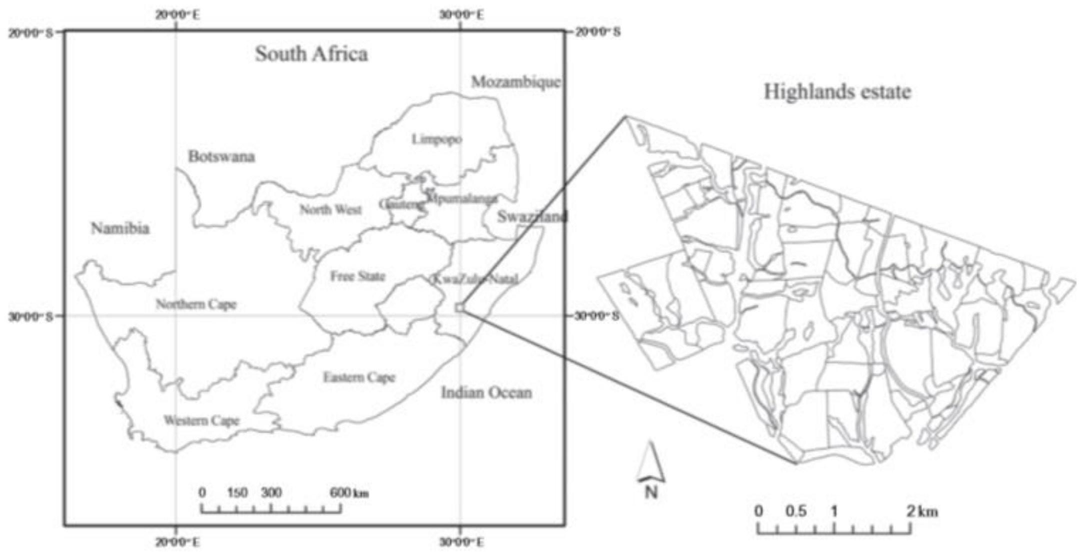

Figure 1. Map showing the location of the study site

Site selection

Based on site quality three *Eucalyptus grandis* compartments were identified. The productivity of commercial forest sites in South Africa is classified using factors such as geology, topography, climate, soils, and biotic factors (Louw and Scholes, 2002). Consequently, commercial forest sites are reliably differentiated into broad regions of growth potential, i.e. poor, medium, and good (Smith *et al.* 2005). From these identified compartments 5 plots of 20m by 20m were delineated within each site quality for leaf and soil samples collection.

Soil measurements and chemical analysis

At each plot, soil samples were taken at depths of 0-1.2m using a soil auger. These depths were selected because the study area contains shallow soils. Soil samples were collected under the homogeneous foliar cover. The soil samples were taken 1m apart in a transect at opposite directions from the centre tree in a 20m by 20m plot. A total of 60 soil samples were collected and transported back to the laboratory for carbon determination. The soil samples were air-dried for at least 48 hours and sieved through a 2mm screen, bottled, and labelled; subsequent analytical determinations are expressed on an oven-dry mass basis. Soil carbon was determined through the combustion of the sample in a ceramic boat in a high temperature furnace at 1100 ^{0}C. The resultant combustion gases were carried under a flow of helium gas and passed through a thermal conductivity cell. The soil C content is expressed as a percentage of the oven-dried soil sample (Bremner and Mulvaney 1982).

Table 1. The descriptive statistics of the soil carbon (%) data set used in the analysis

Variable	Mean	Minimum	Maximum	Standard Deviation	Number of samples
Soil carbon	0.7261	0.4554	1.4114	0.1688	60

Leaf spectral measurements

Leaf samples were gathered from the sunlit branches using tree climbers. Leaf spectral measurements were acquired using an ASD spectroradiometer (Fieldspec3 Pro), fitted with a 25° field-of-view, with a leaf clip attached to the fore-optic. The ASD field spectroradiometer senses in the spectral range of 350-2500nm, with a bandwidth of 1nm. This procedure of using a leaf clip and contact probe serves to shield the leaf sample from ambient light and guarantees constant illumination and viewing geometry (Castro-Esau *et al.* 2006). Radiance measurements were converted to target reflectance using a calibrated white spectral panel on the leaf clip. Reflectance measurements were taken by averaging 50 scans with a dark current correction at every spectral measurement.

Spectral transformation

Continuum removal transformations were applied to the resulting spectra to normalizes reflectance spectra in order to allow for the comparison of individual absorption features from a common baseline (Kokaly 2001, Noomen *et al.* 2006, Wu *et al.* 2008) and the resultant curves have values ranges between 0 and 1, in which the absorption troughs are enhanced (Schmidt and Skidmore 2001).

Statistical analysis

PLS and Variable Importance in Projection (VIP) were used to select the significant bands for the prediction of soil C content from the raw reflectance and continuum-removed spectra. PLS is a well-known statistical procedure that combines concepts from multiple linear regression and principal component analysis. It reduces the full spectrum to a smaller number of non-correlated components, called latent variables, that contain the most useful information (Rosipal and Trejo 2001, Kooistra *et al.* 2004, Feudale and Brown, 2005, Nguyen and Lee, 2006). In order to simplify the modelling process, the smallest number of narrow-bands that offered the best predictive performance for estimating soil C was identified, using a ranking technique based on the bootstrap method. The significantly correlated bands for both raw and continuum-removed spectra were bootstrapped with soil C and ranked using r (high to low) and the standard error of the mean (SE; low to high). The best 35 bands were further used in the model building process, which required robust validation. These 35 bands were selected to justify the central limit theorem (delMas *et al.* 1999).

Model validation is the most important step in the model development process if models are to be accepted for operational use and decision making. There are various established approaches to model validation, e.g., validation based on an independent test data set and cross-validation procedures, also called leave-one-out methods. Ideally, validation based on independently gathered data is highly recommended, but is often expensive and time consuming (Tesfamichael *et al.* 2009). A cross-validation procedure was adopted in this study and the error of prediction (RMSE) and coefficient of determination (R^2) were reported

Results

Correlations between soil carbon and leaf spectra

The results of the univariate correlation test between soil carbon and leaf spectra, i.e., raw and continuum-removed spectra, are shown in Figure 1 and Figure 2, respectively. The leaf raw reflectance spectra and continuum-removed leaf spectra were significantly correlated with soil carbon concentrations in the shaded wavelength regions ($p<0.05$). From this result we noted that only 224 bands were significantly correlated (r varied between ±0.26 and ±0.33) with soil C from the possible 2150 lead raw spectra, while only 129 continuum removed leaf spectra were significantly correlated (r varied between ±0.26 and ±0.74) with soil C.

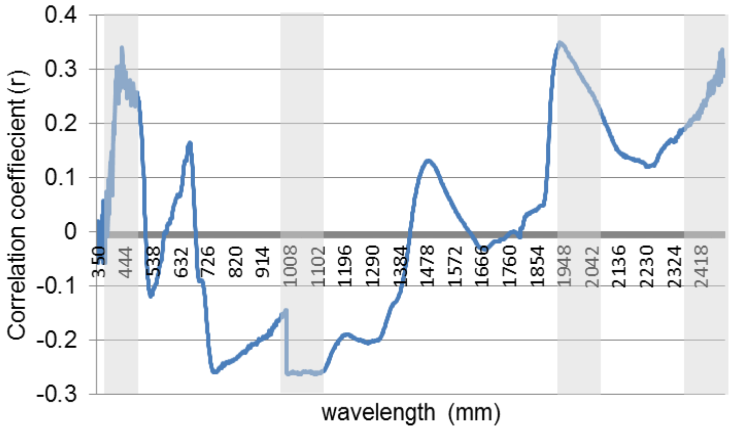

Figure 1. A graph showing the univariate correlation test between soil carbon and raw spectra

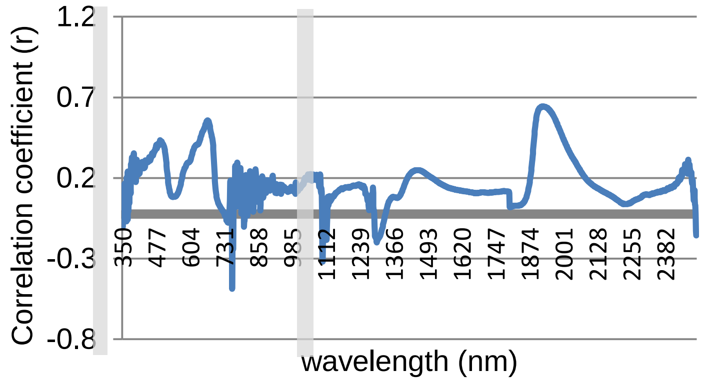

Figure 2. A graph that shows the univariate correlation test between soil carbon and continuum-removed spectra

Furthermore, the relationships between soil carbon and raw and continuum-removed leaf spectra were further assessed for robustness using a bootstrapping method. Bootstrapping statistics (Tables 2 and 3) confirmed the robustness of the relationships through mean r values above 0.60 for the selected wavelengths. The first 35 wavelengths that returned high bootstrapped correlation coefficients (*p<0.05*) for both raw and continuum-removed spectra were adopted as VIP and were used in the subsequent soil carbon model development process.

Table 2. The 35 VIP data from raw spectra

Wavelength	Importance	*r*	SE (%)
1910	1	0.259	0.036
1911	2	0.264	0.034
1912	3	0.269	0.035
1913	4	0.274	0.035
1914	5	0.279	0.003
1915	6	0.284	0.035
1916	7	0.288	0.003
1917	8	0.295	0.003
1918	9	0.296	0.034
1919	10	0.299	0.034
1920	11	0.302	0.033
1921	12	0.305	0.003
1922	13	0.308	0.003
1923	14	0.311	0.035
1924	15	0.313	0.035
1925	16	0.315	0.033
1926	17	0.316	0.033
1927	18	0.319	0.003
1928	19	0.321	0.003
1929	20	0.322	0.034
1930	21	0.322	0.033
1931	22	0.324	0.032
1932	23	0.328	0.033
1933	24	0.329	0.033
1934	25	0.382	0.032
1935	26	0.382	0.033
1936	27	0.332	0.035
1937	28	0.334	0.033
1938	29	0.333	0.031
1939	30	0.336	0.033
1940	31	0.333	0.034
1941	32	0.335	0.032
1942	33	0.335	0.031
1943	34	0.334	0.032
1944	35	0.334	0.032

Table 3. The 35 VIP data from CR spectra

Wavelength	Importance	*r*	SE (%)
1955	1	0.675	0.058
1954	2	0.681	0.059
1956	3	0.676	0.006
1653	4	0.682	0.059
1957	5	0.675	0.059
1952	6	0.685	0.058
1958	7	0.673	0.059
1951	8	0.684	0.058
1950	9	0.685	0.058
1959	10	0.671	0.062
1949	11	0.687	0.057
1960	12	0.671	0.061
1961	13	0.668	0.059
1948	14	0.688	0.057
1947	15	0.689	0.06
668	16	0.727	0.041
1962	17	0.665	0.062
667	18	0.724	0.041
669	19	0.731	0.042
670	20	0.735	0.042
666	21	0.714	0.041
1946	22	0.693	0.057
665	23	0.714	0.004
1963	24	0.664	0.061
671	25	0.737	0.041
1945	26	0.692	0.055
664	27	0.710	0.042
1944	28	0.692	0.058
1964	29	0.662	0.059
672	30	0.739	0.042
1965	31	0.660	0.062
663	32	0.701	0.041
1943	33	0.695	0.056
1966	34	0.656	0.064
673	35	0.746	0.039

Soil carbon model development from raw canopy spectra

Figure 3 shows the models developed from all significant bands and the best 35 VIP bands as produced by PLS regression. The model developed using the best 35 bands, based on *r* and SE, boasted a distinct improvement coefficient of determination (R^2 =0.71) and RMSE = 0.1032 %, when compared to the R^2 = 0.63 and RMSE = 0.111% from the model generated using these 224 wavelengths. The VIP (Table 2) of bands that exhibited significant contributions (*p<0.05*) in the model building were located in the visible and shortwave-infrared regions of the electromagnetic spectrum.

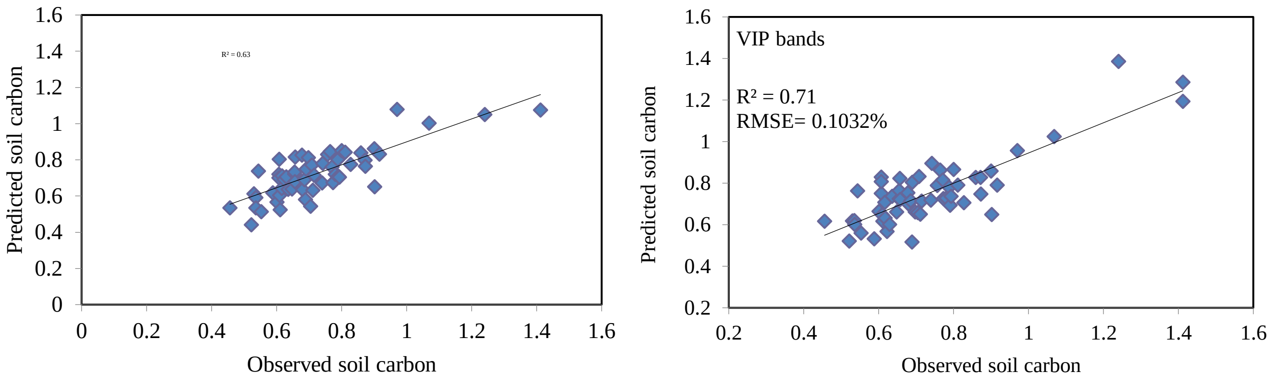

Figure 3. Comparison of observed and predicted soil C models developed from all significant bands and the 35 VIP bands of raw canopy spectra

Soil carbon model development from continuum-removed spectra

The model developed from the 35 selected bands returned a distinctly higher coefficient of determination (R^2 = 0.91) and RMSE (0.04459%), compared to the model with all VIP bands (R^2 = 0.77, RMSE = 0.0639%). The importance of bands that exhibited significant contributions (*p<0.05*) in the model building is shown in Figure 4. The majority of these bands were located on the SWIR region of the electromagnetic, which is known for absorption features related to organic matter (Bartholomeus *et al.* 2008).

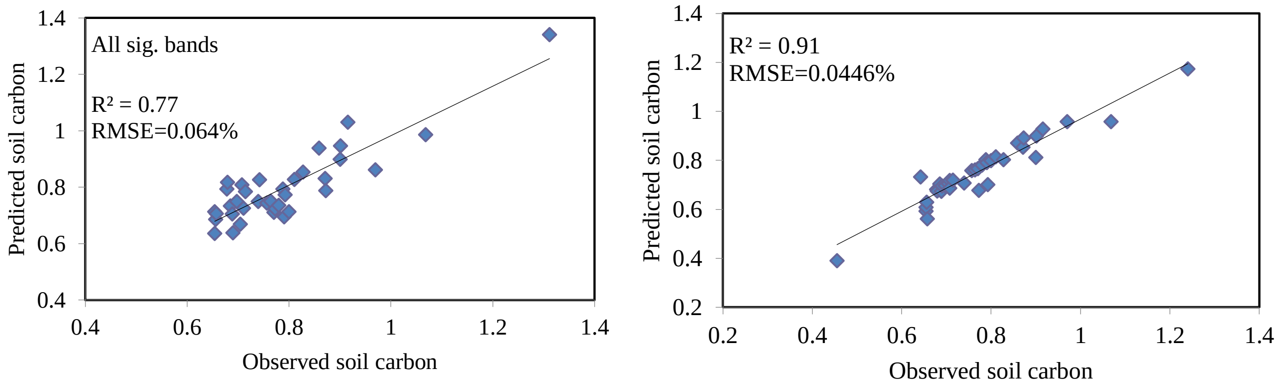

Figure 4. Comparison of observed and predicted soil C models developed from all significant bands and the 35 VIP bands of continuum removed spectra

Discussion

Soil carbon content is an important soil fertility attribute in the South African commercial forestry industry and arguably is the one specific soil property that is constantly impacted by the site management undertaken prior to planting (O'Hehir and Nambiar 2010). The need for continuous assessments of soil carbon content throughout the rotational period, e.g., for carbon sequestration studies and other research related work, dictates that state of the art technologies be used for quicker operational predictions to be achieved. This study assessed the suitability of canopy spectra, derived from spectroradiometer data, for estimating soil carbon content of *Eucalyptus* clones in KwaZulu-Natal, South Africa.

Assessing relationships between soil carbon content and canopy spectra

The relationships between plant canopy nutrient content and soil chemical nutrients is important as benchmarks for assessment of plants' ability to respond to fertilizer treatments, and associated optimum growth returns (Schönau and Herbert ,1989). In this study, significant ($p<0.05$) correlations were obtained between soil carbon and canopy spectra, i.e. raw and continuum-removed spectra (Figure 1 and 2). Research has previously shown that continuum-removed spectra enhances and transform differences in the shape of absorption features of interest (Weng *et al.* 2010). This is further illustrated in the model robustness for the continuum-removed spectra, as shown in the correlation range. The continuum-removed spectra yielded better correlation ranges ($\pm0.26 > r > \pm0.74$, $p<0.05$) compared to raw spectra ($\pm0.26 > r > \pm0.33$, $p<0.05$). These relationships were mostly located on the visible (400–700nm) and short-wave infrared bands (SWIR), specifically the 1955–1965nm, 2215nm, 2265nm, 2285–2295nm, and 2315–2495nm regions of the ASD-acquired spectra. Previous research, e.g., Henderson *et al.* (1992), Ben-Dor *et al*. (1997), Shepperd and Walsh (2002), and recently, Bartholomeus *et al.* (2008), Summers *et al*. (2011) have shown that these wavelengths yielded the highest correlation with soil organic carbon. Furthermore, these wavelength regions are associated with organic matter absorption features, and by extension, to soil carbon as one of the key derivatives/indicators of decomposing organic materials. Overall, the success illustrated in this study and other related studies in estimating soil fertility properties from canopy spectral features, e.g., Aitkenhead-Peterson *et al.* 2006, Albrechtová *et al.* 2008, and Mzinyane *et al* (2015), should not be ignored, given the interrelationships that exist between the amount of nutrients in the soil and their impacts on vegetation health and associated expression in canopy-level foliar spectral measurements (Schönau and Herbert 1989). Such research efforts provide scientists with innovative research methods, given the ever-improving imaging spectroscopy sensors which are envisaged to provide better and enhanced soil property mapping and modelling approaches than previously imagined (JPL, 2010).

Model development, comparison, and validation

The purpose of developing models for any given parameter, i.e., dependent variable, is to enable future estimations and assessments, ideally at synoptic scales, using the developed models. The models in this study were developed to estimate soil carbon from the raw and continuum-removed spectra using a PLS regression approach. The continuum-removed model yielded higher adjusted R^2 and lower RMSE values compared to the model based on raw spectra (Figures 3 and 4). Previous studies have shown the advantages of using spectral transformations over raw spectra (Fourty and Baret 1998, Yoder and Pettigrew-Crosby 1995, Cho and Skidmore 2006). These advantages range from enhanced absorption features of foliar biochemical concentrations to minimizing effects such as atmospheric, soil background, and water absorption and most importantly data redundancy. A recent study suggested that continuum-removed spectral can yield higher estimates of soil nitrogen compared to raw spectral data (Mzinyane *et al.* 2015).The exclusion of wavelengths based on the bootstrap r and SE ranks resulted in improved adjusted R^2 values with low RMSE values, when compared to models with all VIP selected bands. Previous studies that have attempted to predict various soil chemistry parameters using canopy foliar spectra reported encouraging results (e.g., Ollinger *et al.* 2002). However, the lack of studies which relate foliar spectral characteristics to soil fertility parameters is a cause for concern. Most of the reported studies, except for those of Ollinger *et al.* (2002), Aitkenhead-Peterson *et al.* 2006, Albrechtová *et al.* 2008, and Mzinyane *et al* (2015), were based on bare soil spectra collected under either laboratory or field conditions. The leaf and canopy level models developed here and elsewhere should be expanded and tested robustly for future operational and management practices. Such models have the distinct advantage of being extensible to synoptic assessments at an operational scale, albeit after regional or even site-specific calibration.

Implications of these results for terrestrial systems

As mentioned above, the results obtained in this study have significant implications for spatially and temporally continuous management and monitoring of soil C using leaf and canopy spectral features over large spatial domains (e.g., Luo *et al.* 2008, Ben-Dor *et al.* 2009, and Mashimbye *et al.* 2012). These results emphasize the need to integrate vegetation cover in future soil fertility parameter estimations, because vegetation importance in soil erosion, land degradation, and climate change mitigation studies is well documented (Le Roux and Sumner 2013). The resultant maps of specific soil fertility parameters will benefit various land users (such as farmers, foresters, environmentalists and agronomists) and provide early detection of any physiological change before damage of potentially catastrophic proportions are visible to the naked eye. Thus, research initiatives that seek to frequently assessment soil fertility under the given the threats posed by climate change, will be enhanced due to the potential for synoptic visualization of soil fertility status over large areas.

Conclusions

This study demonstrated that canopy spectra can be used as proxy for soil carbon content, based on the causal relationship that exist between soil nutrients and plant growth, i.e., leaf nutrient content. The continuum-removed model performed better than the raw spectra model. Since this is first study to explore this foliage-soil approach according to our knowledge, there is a need to test the applicability of using airborne imaging spectroscopy remote sensing data such as HyMap, to acquire large spatial area coverage and to better understand the landscape variability of soil C and other soil fertility parameters at air or space platform. This study demonstrated that most of the canopy spectral bands which are sensitive to soil C are located in the VIS and SWIR spectral regions. A need exists to test how the relationship between canopy spectra and soil fertility parameters can be used to understand the productivity of various crops and also grazing patterns of animals in an ecosystem. Such studies could play a crucial role in determining critical soil fertility values and associated fertilization needs, which aid land managers to mitigate poor growth conditions and adverse effects on the ecosystem and habitats, in general.

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