Light reflectance provides rapid assessment of soil quality

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Abstract

The global threat of environmental problems cannot be reliably assessed without methods for rapid measurement of soil quality. Here, we demonstrate rapid and simultaneous prediction of a number of soil quality attributes for over 1000 African soils from measurement of light reflectance spectra. User prediction accuracy was 70–88% for soil carbon, clay, and cation retention capacity, and user sensitivity was >77% for several widely-used soil fertility capability tests. Site-level, management-induced variation in soil properties and crop yields were also predicted. These advances will greatly improve scientists' ability to assess soil problems using calibrations based on a small number of selected soils.

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1. **Introduction**

Degradation of soil quality poses a serious threat to human welfare and the environment (*1–3*). However, a lack of easily measurable attributes that reflect the capacity of soil to perform specific production or environmental functions makes broadscale quantitative assessment difficult (*4, 5*). Conventional assessments of soil quality rely on local calibration of soil performance to soil laboratory tests, but these analyses are expensive and large numbers of samples are required to adequately characterize spatial variability (*4*). Advances in infrared spectroscopy and chemometrics have created new possibilities for rapid non-destructive assessment of soil constituents (*6–12*), but their routine application is limited (*13–15*). We investigated whether measurement of diffuse reflectance spectra can be used for the direct assessment of soil quality. As a basis for these investigations, we established a spectral library of a diverse range of archived African topsoils (*16*) for which standard soil analyses were available (*17*). The soils were derived from various studies conducted in Malawi, Kenya, Rwanda, Tanzania, Uganda, Zambia, and Zimbabwe. Spectral readings were taken on air-dried soil fines using a portable spectrometer and an artificial light source (*18*).

2. **Prediction of soil properties**

Basic soil physical and chemical properties showed high correlation with the derivative reflectance values located around the principal absorption features in the visible (0.4 – 0.6 μm) and short wave infrared (1.4, 1.9, 2.2, 2.3, 2.4 μm) wavelength regions (Fig. 1).

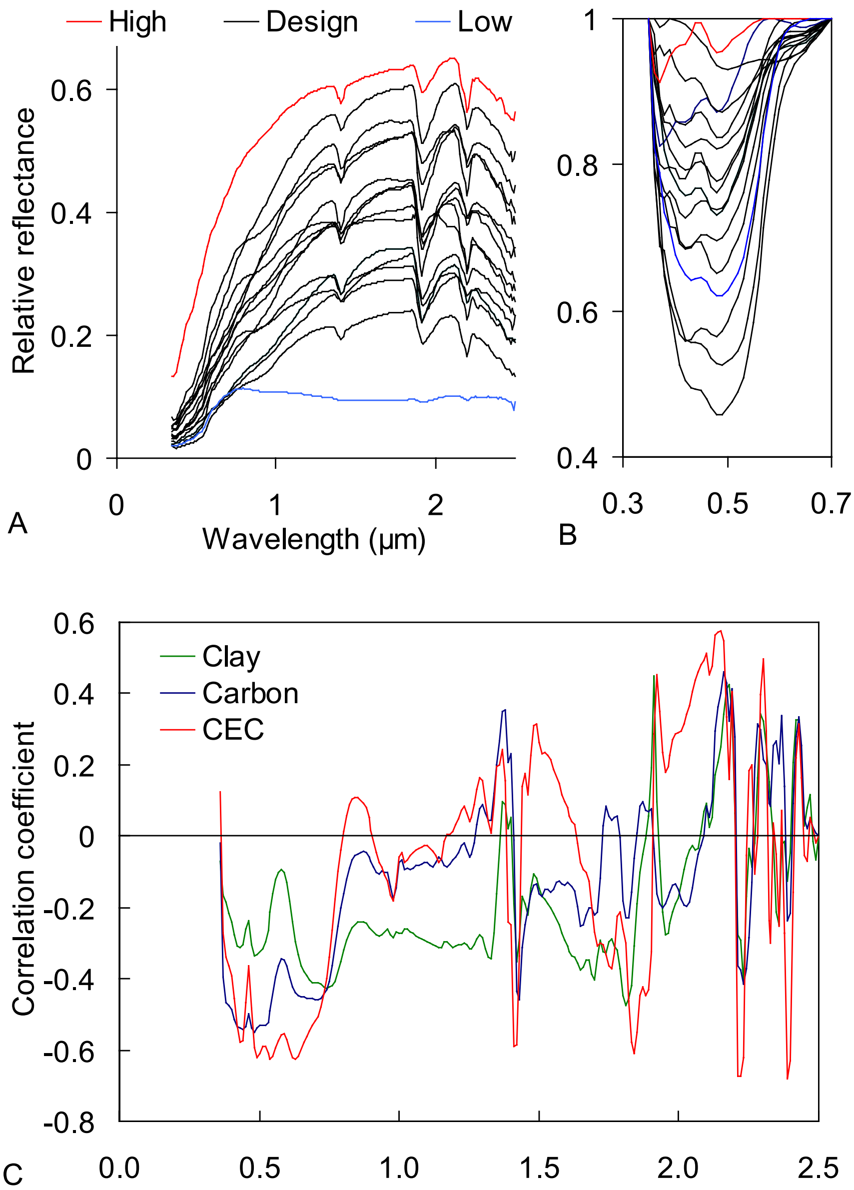

Fig. 1. Diffuse reflectance spectra from the Africa soils library. (**A)** Samples with smallest Euclidean distance to central composite design points (Design) for the first three principal components of the entire soils library (n=1170) and the spectra with highest (High) and lowest (Low) average albedo. (**B**) The visible wavelength part of the spectra shown continuum removed to emphasize the absorption features. (**C)** Correlation of soil carbon and clay concentrations and effective cation exchange capacity (CEC) with the first derivatives of the relative reflectance at different wavelengths.

Soil carbon, effective cation exchange capacity (CEC) and particle size distribution could be predicted from the soil reflectance spectra with sufficient accuracy (validation r^2 0.70 – 0.88) for landscape studies and farm advisory work (Table 1). Because these properties are often used in pedotransfer functions and models to predict important soil functional attributes for agricultural, environmental and engineering applications (*4*), such functional attributes should calibrate directly to reflectance spectra. For example, using pedotransfer functions based on particle size distribution to predict available water holding capacity (*19*) and soil erodibility (*20*), predictions from spectra gave validation r^2 values of 0.75 and 0.76, respectively.

3. Prediction of soil tests

One of the most important functional attributes of soils is their capacity to support plant growth. The African library was used to test how well soil reflectance spectra could classify soils with respect to critical values for widely-used tests (*21, 22*) for soil fertility capability (Table 1). The reflectance spectra correctly classified 77 – 96% of positive test samples and 69 – 83% of negative test samples in the validation data sets. These results demonstrate the feasibility of using reflectance spectrometry for broad diagnosis of soil fertility constraints and prediction of plant response to specific soil ameliorants in tropical and sub-tropical African soils.

Table 1. Prediction success for soil attributes in the Africa soils library.

Prediction success using partial least squares regression (*29*)

Soil attribute	r^2_{cal}*	r^2_{val}*	SEP†	No. of soils	Min	Median	Max
CEC‡ ($cmol_c\ kg^{-1}$ soil)	0.91	0.88	3.6	1109	0.4	8.0	55
Soil carbon ($g\ kg^{-1}$ soil)	0.80	0.70	4.0	1011	2	12	56
Clay ($g\ kg^{-1}$ soil)	0.90	0.77	72	682	50	400	790
Sand ($g\ kg^{-1}$ soil)	0.88	0.70	117	682	80	370	900
CEC_{clay} ($cmol_c\ kg^{-1}$ clay)	0.89	0.88	7.4	666	3.1	37	95

Prediction success for soil tests using classification trees (*30*)

Soil test	Sensitivity§	Specificity‖	n_{pos}¶	n_{neg}#	No. of soils	Min	Median	Max
pH(water) <5.5☆	85	79	69	295	1135	4.2	6.0	10.0
Acidity saturation >30% of CEC††	96	79	24	333	1109	0	0	94
Extractable P <7 $mg\ kg^{-1}$‡‡	82	69	244	127	1152	0.1	3.7	330
Extractable P >15 $mg\ kg^{-1}$§§	82	83	77	294	1152	0.1	3.7	330
Exchangeable K <0.2 $cmol_c\ kg^{-1}$‖‖	83	72	109	262	1152	0.03	0.3	6.2
Exchangeable K >0.4 $cmol_c\ kg^{-1}$¶¶	78	83	161	210	1152	0.03	0.3	6.2
Mineralizable N >4.1 $mg\ kg^{-1}\ d^{-1}$##	77	70	106	188	920	-2.8	2.8	45

*Coefficients of determination for observed versus fitted values for calibration and validation sample sets. A sample of one-third of the total soils library was withheld for validation. †Standard error of prediction. ‡Unbuffered cation exchange capacity calculated as sum of cations and exchangeable acidity. §Percentage of positive test values correctly classified in validation sample. A random sample of one-third of the total soils library was withheld for validation.‖Percentage of negative test values correctly classified in validation sample. ¶Number of soils in validation sample with positive test value. #Number of soils in validation sample with negative test value. ☆Strong soil acidity. ††Moderate to high levels of Al toxicity. ‡‡Food grain crops typically respond to P additions. §§Few crops respond to P additions. ‖‖Crop response to K additions expected. ¶¶ Crop response to K additions unlikely. ## The one-third of our samples with the highest potentially mineralizable N (>4.1 mg N $kg^{-1}\ d^{-1}$) were assumed to be less likely to respond to N fertilization than samples with lower test values.

4. Prediction of crop productivity

Data from a soil management experiment conducted at 29 sites in southern African (*23*) were used to test whether crop productivity across sites within specific agroecological zones could be calibrated to soil spectra. When agroecological zone (n=3) and soil management treatment (n=4) were controlled using graphical modeling (*24*), maize (*Zea mays* L.) grain yields (range 0.003 – 9.2 Mg ha^{-1}) were related to soil carbon (r^2=0.67) and exchangeable bases (r^2=0.61). Calibrations with soil reflectance spectra produced cross-validated r^2 values of 0.94 for exchangeable bases (range 0.4 – 35.4 $cmol_c$ kg^{-1}) and 0.87 for soil carbon (range 4 – 22 g kg^{-1}). Accordingly, yields were strongly related to the first three principal components of the soil reflectance spectra (r^2=0.70). These results provide good prospects for the calibration of inherent soil fertility capability to soil reflectance spectra within specific agroecological zones.

5. Prediction of management-induced changes in soil quality

Archived soils from long-term field experiments were used to further test whether variation in soil fertility within sites induced by soil management could be related to soil spectra. In an 18-year field experiment in Kenya testing different levels of fertilizer, manure and crop residue management (*25*), high cross-validated r^2 values (0.77 – 0.82) were obtained for prediction of soil fertility attributes and crop yields from spectra (Table 2). In a further test at two sites in Kenya (*26*) the effects of only 18 months of contrasting land uses on the light fraction (>150 μm and <1.13 Mg m^{-3}) of soil organic matter (range 0.1 – 2.7 g kg^{-1} soil; n=32) were strongly related to the reflectance spectra (cross-validated r^2=0.81). These results demonstrate that it is feasible to develop site-specific calibrations between management-sensitive attributes of soil quality for crop production and soil reflectance spectra.

Table 2. Prediction success in an 18-year soil management experiment.

Soil attribute	r^2_{cal}*	r^2_{val}*	SEP†	Min	Max
Exchangeable bases ($cmol_c\ kg^{-1}$ soil)	0.90	0.81	0.796	6.3	12.8
Light fraction OM‡ ($g\ kg^{-1}$ soil)	0.89	0.78	0.288	0.8	8.2
Microbial biomass C ($mg\ kg^{-1}$ soil)	0.90	0.80	11.8	40	133
Bean yield§ (Mg grain ha^{-1})	0.91	0.82	0.092	0.22	1.01
Maize yield§ (Mg grain ha^{-1})	0.88	0.77	0.535	1.65	5.39

*Coefficients of determination for observed versus fitted values for calibration (n=31) and full cross-validation sample sets. †Standard error of prediction. SEP for light fraction soil organic matter (SOM) is presented for $\log_e$ transformed data. ‡Light plus medium Ludox fraction of organic matter >250 µm size and <1.37 Mg m^{-3} density. §Long-term average grain yields. Maize (*Zea Mays* L.) and beans (*Phaseolus vulgaris* L.) were grown once each year in rotation.

6. A new approach to soil evaluation

The results amplify previous findings showing the promise of reflectance spectrometry in soil studies (*6–15*) and point to a new approach to soil evaluation, based on direct calibration of soil performance to spectral libraries. Because the spectral technique allows large numbers of samples to be rapidly analyzed, resources can be directed towards thorough characterization of the soil spatial variability within a target region. Experiments to develop direct calibrations for various soil functions can then be conducted on a small number of benchmark soils or sites, selected to represent the variation in the spectral library (e.g. Fig. 1). For example, a calibration set of only 80 soils, selected on the basis of their spectral properties, was adequate to predict CEC for the entire Africa soils library (validation r^2 = 0.80 for the remaining 1017 library samples). Similarly, a classification tree with a single splitting node developed from only 30 selected spectra (twice replicated composite design) gave good success (sensitivity of 80% and specificity of 81%) in predicting low CEC values (<4 $cmol_c$ kg^{-1}) for the library.

7. Conclusion

The spectral library approach makes it possible to generalize the results from soil assessments that are conducted at a limited number of sites, and expands opportunities for using multi- and hyperspectral remote-sensing (*6, 27, 28*). Functional attributes that are expected to calibrate well to soil reflectance spectra include: inherent plant productivity, soil toxicity and nutrient limitations to plant growth, soil erodibility, soil compressibility and shrinkage, water retention and conductivity, and capacity to adsorb wastes and pollutants. These advances will greatly improve scientists' ability to address global environmental issues such as land degradation and carbon sequestration.

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16. The library soils consisted of topsoil (0-15 or 0-20 cm depth) samples, for which basic soil properties had been analyzed by the ICRAF soil laboratory, from multi-location experiments, on-farm trials and surveys conducted in eastern and southern Africa during 1993–1999. The library included both cultivated and uncultivated soils falling in the Soil Taxonomy orders Alfisols, Andisols, Aridisols, Entisols, Histosols, Inceptisols, Mollisols, Oxisols, Ultisols and Vertisols.

17. All soil analyses were conducted by the ICRAF soil laboratory using standard methods (*25, 26*).

18. Soil diffuse reflectance spectra were recorded for each library sample using a FieldSpec™ FR spectroradiometer (manufactured by Analytical Spectral Devices Inc, Boulder, Colorado) at wavelengths from 0.35 to 2.5 µm with a spectral sampling interval of 1 nm. Soil samples were illuminated with one or two Tungsten Quartz Halogen filament lamps (50W bulb; ~3200 K color temperature) in housings with aluminum reflectors placed at a 30º zenital angle and at a distance of 50 cm from the sample. Reflected light was collected with a 25º field-of-view foreoptic at a distance of 5 cm from the sample, at a 30º zenital angle and perpendicular to the plane of illumination. Air-dried soil samples ground to pass a 2-mm sieve were packed in 12-mm deep, 55-mm diameter polystyrene petri dishes, ensuring a flat soil surface, flush with the top of the dish. Reflectance spectra were recorded at four positions by successively rotating the sample through 90º. Ten spectra were recorded at each position and averaged. Before reading each sample ten white reference spectra were recorded using calibrated spectralon (Labsphere®, Sutton, New Hampshire) placed at the same distance as the soil sample. Reflectance readings for each wavelength band were expressed relative to the average of the white reference readings. Typical coefficients of variation in average reflectance are about 1% among rotations within a sample dish, and 2% for replicate dishes from a soil sample. Calibrations with soil variables were done on the first derivatives of the reflectance spectra, resampled to 10 nm wavelength intervals. With this method, a single operator can comfortably analyze several hundred samples a day.

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29. Partial least squares regression was conducted using Unscrambler® (Camo ASA, Oslo). Variables were first divided into two to four groups using regression trees CART® (Salford Systems, San Diego State University, USA) and PLS regressions developed separately for each group. The predicted values were then combined.

30. Classification trees were constructed using CART®.

31. We are grateful to the authors of *25* and *26* and the Kenya Agricultural Research Institute for access to their data archives. We thank the Rockefeller Foundation and the Swedish International Development Cooperation Agency for financial support.

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