Sensing Soil Quality:

The Evidence From Africa

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Abstract

The potential of diffuse reflectance spectrometry (DRS) as a rapid integrated measure of soil quality for plant production was demonstrated using a comprehensive spectral library (0.35-2.5 μm) of African soils. In controlled soil management experiments, soil reflectance convolved to Landsat 5 wavelength band-passes correlated with various soil quality attributes (r^2 range, 0.26-0.82) and crop yields (r^2 range, 0.30-0.80). Using 10 nm wavelength bands, soil reflectance correlated well with basic properties (r^2 range, 0.66-0.90) of a wide diversity of soils. We show how DRS can be used with ground observations and Landsat 5 imagery to determine the spatial variation in soil properties. DRS could help with prediction of various soil functions, such as carbon sequestration potential.

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1. Soil Quality Assessment

Degradation of soil quality has negative impacts on agricultural productivity, ecosystem and atmospheric change, and water and habitat quality (*1,2*). The major soil degradation processes are accelerated soil erosion, depletion of soil organic matter, soil nutrients, and the deterioration of soil structure. It has been estimated that the degraded area of the world's arable land increased from 10% in the early 1970s to about 40% in the early 1990s (*1*). The greatest need for remediation is in developing regions of the world, where the rate of loss of agriculturally usable land has been estimated at 0.3% per year (*2)*. In order to effectively manage the soil resource base, land managers require more reliable and cost-effective assessments of soil quality over time and space.

In general, quantitative assessments of soil quality and degradation are hampered by a lack of easily measurable attributes that reflect the capacity of soil to perform specific production, environmental or ecological functions (*3*). Soil quality is most commonly assessed in the laboratory using soil physical, chemical and biological properties as proxies for soil functional attributes. Generally, several soil properties are required to characterize a particular soil function. This is time-consuming, expensive and large numbers of samples are required to quantify the spatial and temporal variability of an area (*4*). In developing countries resources to support such assessments are limited. Most importantly, sets of soil quality indicators developed for a specific purpose generally do not provide inference about the capacity of soils to perform other functions (*3*).

Thus we urgently require methods for assessing soil function that can be cheaply, rapidly and repetitively applied. Ideally, the measurements should be (1) highly sensitive to a broad range of physical, chemical and biological properties of soils and (2) diagnostic of management-induced changes in soil functional attributes at field to landscape levels of observation. We provide evidence here that strongly supports the use of diffuse reflectance spectrometry in this context.

2. Diffuse Reflectance Spectrometry (DRS)

Many components of complex material mixtures (such as those contained in a soil sample) can be distinguished on the basis of their spectral signatures in the solar reflective region. Spectral signatures of materials are defined by their reflectance, or absorbance, as a function of wavelength. Under controlled conditions, the signatures are due to electronic transitions of atoms and vibrational stretching and bending of groups of atoms that form molecules and crystals.

Fundamental features (or modes) in reflectance spectra occur at energy levels that allow molecules to rise to higher vibrational states. The fundamental features related to various components of soil organic matter, for example, generally occur in the mid- to thermal-infrared range (MIR, 2,500-25,000 nm), but their overtones (at one half, one third, one fourth etc. of the wavelength of the fundamental feature) occur in the near- (NIR, 700-1,000 nm) and short wave infrared (SWIR, 1,000-2,500 nm) regions. Soil minerals such as different clay types have very distinct spectral signatures in the SWIR because of strong absorption of the overtones of SO_4^{2-}, CO_3^{2-} and OH^- radicals and combinations of fundamental features of, for example, H_2O and CO_2 (*5*). The visible (VIS, 400-700 nm) region has been widely used for color determinations in soil and geological applications as well as in the identification of iron oxides and hydroxides (*6*).

Recent research has demonstrated the ability of DRS to provide non-destructive rapid prediction of soil physical, chemical and biological properties in the laboratory (*7*, *8*). DRS has also been used in the field, for instance to determine soil organic matter content (*9*). Beyond the discrimination of major soil types, there has been limited success in sensing soil properties directly from satellite multi-spectral and aircraft hyperspectral data however (*7*, *10*). The main inherent problems with imaging spectrometry are sensor spectral resolution, shade and shadow effects, atmospheric interference, and mixtures of materials within pixels (*11*). Thus while there is a growing body of literature related to the application of DRS to soil science there has been little focus on examining the potential of soil reflectance as an integrated indicator of specific soil functions, such as those related to plant productivity. In this study, we investigated the ability of DRS to: (1) determine various soil quality attributes as affected by management and site factors, and (2) provide an integrated measure of soil quality for assessing plant productivity. We also show how DRS measurements can be integrated with ground observations and satellite data to assist spatial prediction of soil erosion risk.

3. Methods

We measured diffuse soil reflectance on archived soil samples from three soil quality management experiments and two on-going ecological studies in eastern and southern Africa:

1. A long-term (18 yr-old) soil management experiment (LTSM) in Kenya in which soil fertility management practices were tested under a rotation of maize (*Zea mays* L.) and beans (*Phaseolus vulgaris* L.). The treatments were examined for their effects on crop yield, soil organic matter fractions and soil chemical properties (*12*).
2. A short-term (2 yr-old) agroforestry experiment (STAF) conducted on two soils in Kenya (Oxisol and Alfisol) to determine the effect of unfertilized, organic-based land-use systems on fractions of soil inorganic and organic P and maize productivity (*13*).
3. A multilocation agroforestry trial (MLAF) conducted during 1993-1994 at 29 sites in Southern Africa (Malawi, Zambia and Zimbabwe) to determine the effect of unfertilized, organic-based land-use systems on soil quality and maize productivity (*14*).
4. A survey of archived agricultural soils (LIB) sampled in on-farm trials and soil surveys from 993 locations in eastern and southern Africa (Kenya, Tanzania, Rwanda, Malawi, Zambia, Zimbabwe). The collection includes up to 993 topsoil (0-15 or 0-20 cm depth) and 410 subsoil samples (up to 1.5 m depth).
5. A study to identify the source area of non-point source pollution in the upland drainage basin of the Kenyan portion of the Victoria Lake Basin in Eastern Africa (LVB). The study is designed to quantify variation in soil degradation due to effects of land use and physiography (*15*).

Soil reflectance and chemical analyses were conducted on air-dried soil samples gently crushed to pass a 2-mm sieve. Soil reflectance was measured using a FieldSpec™ FR spectroradiometer (*16*) at wavelengths from 0.35 to 2.5 µm using a 1 nm spectral sampling interval (*17*). The relative reflectance spectra were resampled to 10 nm bands that are similar to the spectral resolution of currently available airborne imaging spectrometers. We also convolved soil reflectance spectra to correspond to Landsat 5 Thematic Mapper band-passes using ENVI® (*18*) as we are currently using multispectral imagery for characterizing soils in

Africa. All soil analyses were conducted by the ICRAF soil laboratory using standard methods (*12, 13*).

4. Soil Chemometrics

In the controlled experiments, in which soil quality indicators were known to be affected by soil management, we found good relationships ($r^2 > 0.5$) between a number of soil attributes and soil reflectance convolved to Landsat 5 band-passes (Table 1). For instance, in the STAF experiment, despite the short duration of the fallow treatments (17 months), soil relative reflectance explained 26 to 77% of the variation in the soil phosphorus attributes within individual sites (Table 1) and 30 to 98% among the two sites (*20*). In the LTSM experiment, there were strong relationships between simulated Landsat 5 spectra and soil attributes that comprise a small fraction (< 5%) of total soil mass (e.g. light fraction N, $r^2 = 0.78$) and with soil biological properties that normally display high temporal variability (e.g. microbial N, $r^2 = 0.74$). Presumably, soil reflectance is related to differences in the large constituents of organic matter that are in turn strongly related to smaller organic fractions and biological activity. This confers added advantage to soil reflectance measures because small organic soil fractions are frequently difficult to determine analytically and may not be reliable indicators of nutrient availability (*13*).

For some poorly predicted soil attributes, goodness of fit improved dramatically when we used breakpoint (or piece-wise) regression analyses (*21*). For example, the r^2 values for soil nitrate (Table 1) increased from 0.13 to 0.63 (breakpoint 3.5 mg N kg^{-1}) and for extractable P from 0.40 to 0.82 (breakpoint 15.0 mg P kg^{-1}). The use of break-point regression may be justified as the repeatability of certain soil extractions decreases at threshold values that may be inherent in the laboratory technique rather than a function of a lack of explanatory power of the soil reflectance measurements.

Ideal soil quality indicators would not only allow monitoring of the effects of management at a site but also provide basic measurements of soil quality over a wide range of soil conditions (*3*). Using our Africa soils library (Table 2), Landsat 5 simulated reflectance spectra provided significant ($p < 0.001$) relationships, albeit with generally poor fits ($r^2 < 0.5$). Even so, we found a moderately good fit ($r^2 = 0.6$) for effective cation exchange capacity of the clay fraction, which is a good indicator of clay mineralogy, and hence useful for inferring many associated soil properties. However, using 10 nm resolution bandpasses, we obtained good fits for all the soil variables tested (Table 2). The results demonstrate the potential of DRS for detection of both subtle management-induced effects on soil quality within sites and broad differences across sites, and the possibility of using even Landsat 5 simulated spectra with local calibration.

Table 1. Relationships between soil attributes and soil reflectance in soil management experiments. Coefficients of determination (r^2) are for observed versus expected values of soil attributes (0–15 cm depth) predicted from soil reflectance spectra convolved to Landsat 5 band-passes.

Soil Attribute	Study	Method	n	r^2	Min	Max
Total soil N (g kg^{-1})	LTSM	GM[†]	31	0.66	1.4	2.2
Macroorganic matter (g kg^{-1})	LTSM	GM	31	0.70	21	37
Light fraction N (mg kg^{-1})	LTSM	GM	31	0.78	23	126
Medium fraction N (mg kg^{-1})	LTSM	GM	31	0.71	4	75
Heavy fraction N (mg kg^{-1})	LTSM	GM	31	0.71	9	31
Microbial C (mg kg^{-1})	LTSM	GM	31	0.70	40	133
Microbial N (mg kg^{-1})	LTSM	GM	31	0.74	8	24
NaOH organic P (mg kg^{-1})	STAF-1[*]	GM	16	0.68	155	199
NaOH organic P (mg kg^{-1})	STAF-2	GM	16	0.62	62	113
Resin inorganic P (mg kg^{-1})	STAF-1	GM	16	0.34	2.3	4.4
Resin inorganic P (mg kg^{-1})	STAF-2	GM	16	0.77	5.7	18.7
Light fraction P (mg kg^{-1})	STAF-1	GM	16	0.33	0.1	2.2
Light fraction P (mg kg^{-1})	STAF-2	GM	16	0.39	0.1	1.6
Macroorganic matter P (mg kg^{-1})	STAF-1	GM	16	0.26	0.7	4.4
Macroorganic matter P (mg kg^{-1})	STAF-2	GM	16	0.52	0.5	4.4
Soil C (g kg^{-1})	MLAF	CC[‡]	114	0.76	6	32
Soil nitrate (mg kg^{-1})	MLAF	BR[§]	114	0.63	0.01	16.5
Exchangeable K ($cmol_c$ kg^{-1})	MLAF	CC	116	0.65	0.04	0.94
Extractable P (mg kg^{-1})	MLAF	BR	116	0.82	1.3	72.5

[*]STAF-1 is Oxisol and STAF-2 is Alfisol
[†]Graphical model (*17*)
[‡]Canonical correlation analysis
[§]Breakpoint regression analysis

Table 2. Relationship between soil atrributes and soil reflectance for the Africa soils library. Coefficients of determination *(r^2)* for observed versus expected values of soil attributes (0–15 cm depth) predicted from soil reflectance spectra using two spectral sampling methods: Landsat 5 and 10 nm bands. The data set includes topsoils and subsoils from Kenya, Tanzania, Rwanda, Malawi, Zambia, and Zimbabwe.

Soil Attribute	Study	Method	n	r^2 TM	r^2 10 nm	Min	Max
Soil C (g kg^{-1})	LIB	CC	982	0.43	0.83	1.6	50.1
pH (water)	LIB	CC*	982	0.33	0.82	4.2	10
Exchangeable Ca ($cmol_c$ kg^{-1})	LIB	CC	982	0.48	0.90	0.1	35.1
Exchangeable Mg ($cmol_c$ kg^{-1})	LIB	CC	982	0.44	0.86	0.02	12.4
Exchangeable K ($cmol_c$ kg^{-1})	LIB	CC	982	0.33	0.74	0.02	6.2
Extractable P (mg kg^{-1})	LIB	CC	982	0.23	0.64	0.3	328
Mineralizable N (mg kg^{-1} d^{-1})	LIB	PLS†	814	0.12	0.66	-0.5	30.1
Clay (%)	LIB	CC	652	0.42	0.92	5	80
Silt (%)	LIB	CC	652	0.24	0.78	1	40
Sand (%)	LIB	CC	652	0.30	0.90	7	90
CEC per unit clay ($cmol_c$ kg^{-1})	LIB	CC	982	0.60	0.82	1.4	171

*Canonical correlation analysis
†Partial least squares regression

5. Integrated Measurement of Soil Quality for Plant Production

Because many of the soil properties taken to represent soil quality are inter-correlated, we investigated whether DRS could provide an integrated measure of soil quality that relates directly to specific soil functions, here plant production. In the long-term experiment (LTSM), we found significant relationships between treatment factors, maize and bean grain yield and soil reflectance. Soil reflectance (Landsat 5 band-passes) alone explained 72% of the variance ($p < 0.0001$) in long-term maize grain yield (range of 1.6 to 5.4 t ha^{-1}) and 80% of the variation ($p < 0.0001$) in long-term bean yield (range of 0.2 to 1.0 t ha^{-1}). Lower yields were associated with higher reflectance in the near-infrared portion of the spectrum and lower reflectance in the visible range (Fig. 1). Soil relative reflectance in the SWIR range increased by about 0.005 units for each one t ha^{-1} decrease in maize yield.

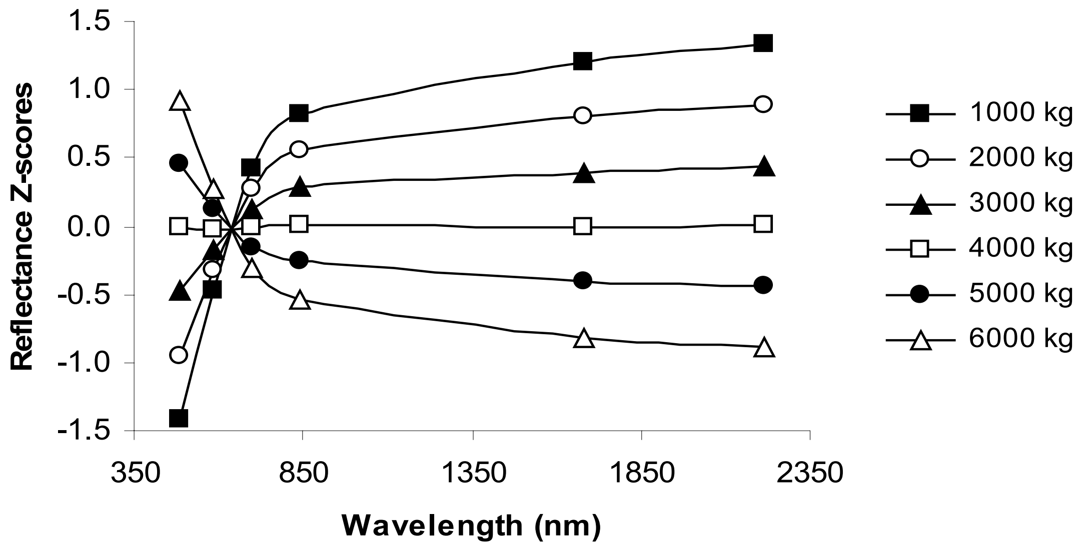

Fig. 1. Soil reflectance responses to variations in long-term average maize yield in a soil management experiment (LTSM). Reflectance spectra are convolved to Landsat 5 band-passes and were predicted from a graphical model. Shown are departures from average reflectance values in units of standard deviations (Z-scores).

In the STAF experiment, yield for the cropping season immediately after treatment was dependent ($p < 0.001$) on total P in macroorganic matter and resin inorganic P, but was conditionally independent of the other measured soil P attributes that were affected by treatment (*13*). Soil relative reflectance alone explained 39 to 67% of the variation in grain yield and increased the explained variance by 9 to 25% when included in the yield model together with the soil P attributes (Table 3). Soil relative reflectance in the SWIR range increased by about 0.005 units for each one t ha^{-1} decrease in maize yield at both sites.

Table 3. Relationships between maize grain yield, soil attributes and soil reflectance in a short-term agroforestry experiment at two locations (STAF). Coefficients of determination (r^2) for observed versus expected values of maize yield predicted from soil attributes (0–15 cm depth) and soil reflectance spectra convolved to Landsat 5 band-passes. Yield ranged from 0.32 to 5.39 t ha^{-1} on the Oxisol and from 0.04 to 2.30 t ha^{-1} on the Alfisol.

Model	Dependent variables included in the models	Method	n	r^2	
				Oxisol	Alfisol
1	Total P in macroorganic matter (mg kg^{-1} soil) Resin inorganic P (mg kg^{-1})	GM*	32†	0.77	0.57
2	Soil relative reflectance	GM	32	0.39	0.67
3	Total P in macroorganic matter (mg kg^{-1} soil) Resin inorganic P (mg kg^{-1}) Soil relative reflectance	GM	32	0.86	0.82

* Graphical model †16 observations at each site

In the MLAF trial, we detected significant interactions between soil attributes, fallow treatment, agroecological zone and maize grain yield for the cropping season immediately after treatment (Fig. 2). The four treatments directly influenced soil nitrate levels as well as maize yields. Nitrate, soil carbon and maize yield levels were also strongly influenced by agroecological zone ($p < 0.01$). The overall model explained 69% of the variation in maize yield ($p < 0.0001$). A similar model based on simulated Landsat 5 soil reflectance spectra, treatment and agroecological zone explained 62% of the variation in post-treatment maize yield ($p < 0.0001$). Again, we observed that soil reflectance as might be seen by Landsat 5 increased as crop yields decreased (Fig 3). In this case, the response in reflectance per unit yield is large because both site as well and soil management factors are involved. When 10 nm bandpasses were screened relative to their explanatory power of post-treatment maize yield, a model based on agroecological zone, treatment and three spectral bands centered on 0.7, 1.0 and 1.9 μm explained 75% of the variation in maize yield.

In summary, each experiment required different soil chemical extractions to describe the major sources of variation in soil quality as indexed by crop performance. In each case it was unknown, *a priori*, which specific attributes were going to be most influential in describing soil quality. Conversely, models based on soil reflectance provided substantial variance reductions in assessments of crop performance in all three experiments and either outperformed or strongly complemented soil quality assessments based on physical and chemical analyses. We also observed soil reflectance responses that consistently shifted toward lower reflectance in the NIR and SWIR regions with increasing crop yield levels.

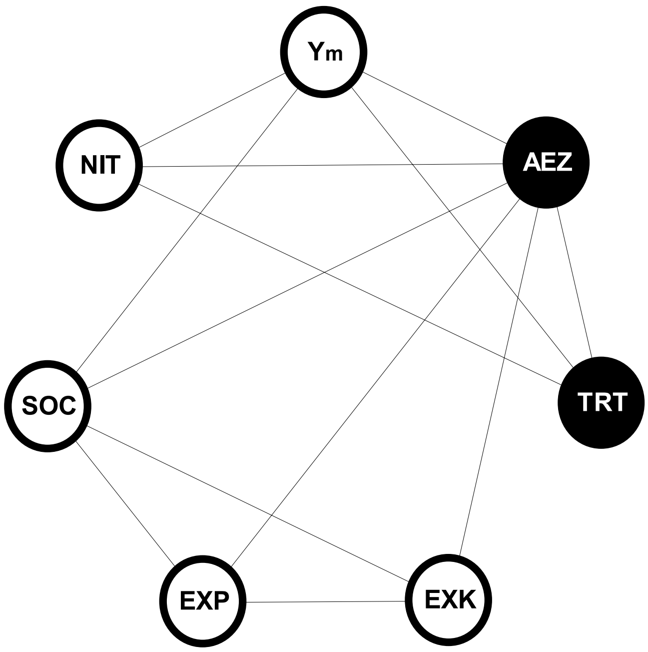

Fig. 2. Graphical model showing conditional dependencies between maize yield and other variables in a multilocation agroforestry experiment (MLAF, *14*). The variables are: maize grain yield during the first season after treatment ($Y_{m,}$ range 0.003 to 9.2 t ha^{-1}), agro-ecological (AEZ, 3 zones), agroforestry treatment (TRT), exchangeable K (EXK), extractable P (EXP), soil organic carbon (SOC) and soil nitrate (NIT). All depicted conditional dependencies are significant at the $p < 0.01$ level.

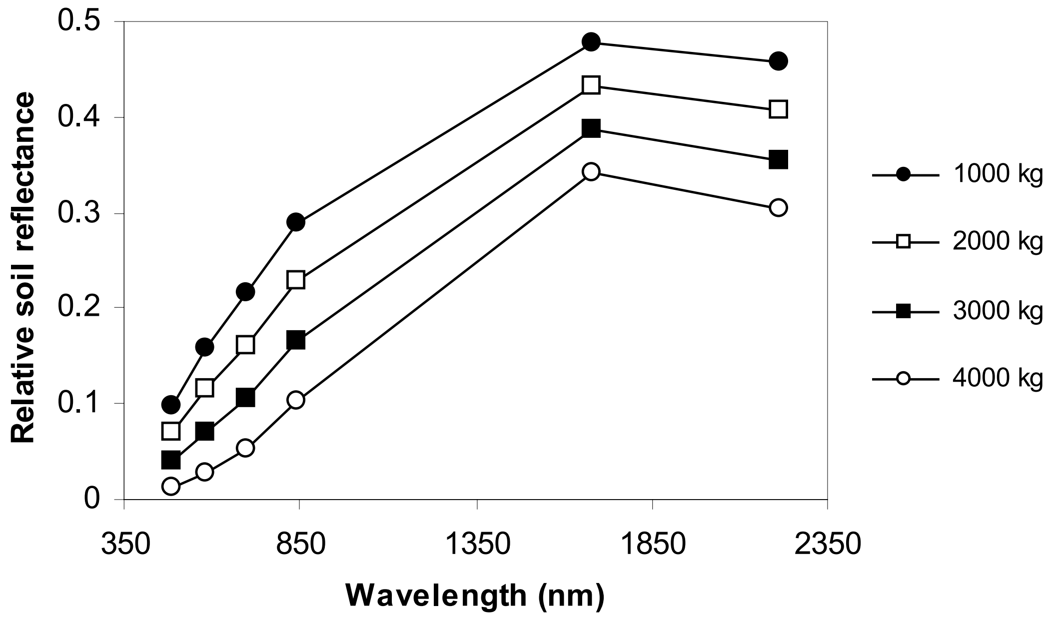

Fig. 3. Modeled response of soil reflectance spectra to variations in maize yield in a multilocation agroforestry experiment (MLAF). The reflectance spectra are convolved to Landsat 5 band-passes.

6. Landscape Level Erosion Risk Assessment

In the Victoria Lake Basin study we used DRS coupled with ground survey and satellite information to prioritize watersheds on the basis of their non-point source pollution potential (*22*). Field-measured soil reflectance spectra were used with Landsat 5 images to identify a large sediment plume in Lake Victoria (Fig. 4) originating from the Nyando River (*23*). A systematic ground survey was initiated in the catchment area of approximately 3,600 km^2 to identify areas where accelerated soil erosion, sediment loading and nutrient leakage were occurring (*24*).

Results for 449 soil surface samples collected indicate that erosion-prone surfaces in the watershed have geophysical characteristics that are highly distinct in terms of their respective soil reflectance values (Fig. 5, Table 4). Graphical model analysis (*19*) revealed that soil erosion surface type was highly dependent ($p < 0.01$) on soil reflectance even after accounting for other principal factors that contribute to site erosion potential such as vegetation cover, land use and slope factors (Fig. 6). Models based on ground reflectance measurements and satellite images (*26*) are helping to target areas that are at high risk for accelerated soil erosion (Fig. 7). This helps to focus both research and development interventions and locate areas where more detailed erosion studies may be warranted. We are using the same method to predict the spatial variation in other soil properties, such as soil carbon, pH and clay content.

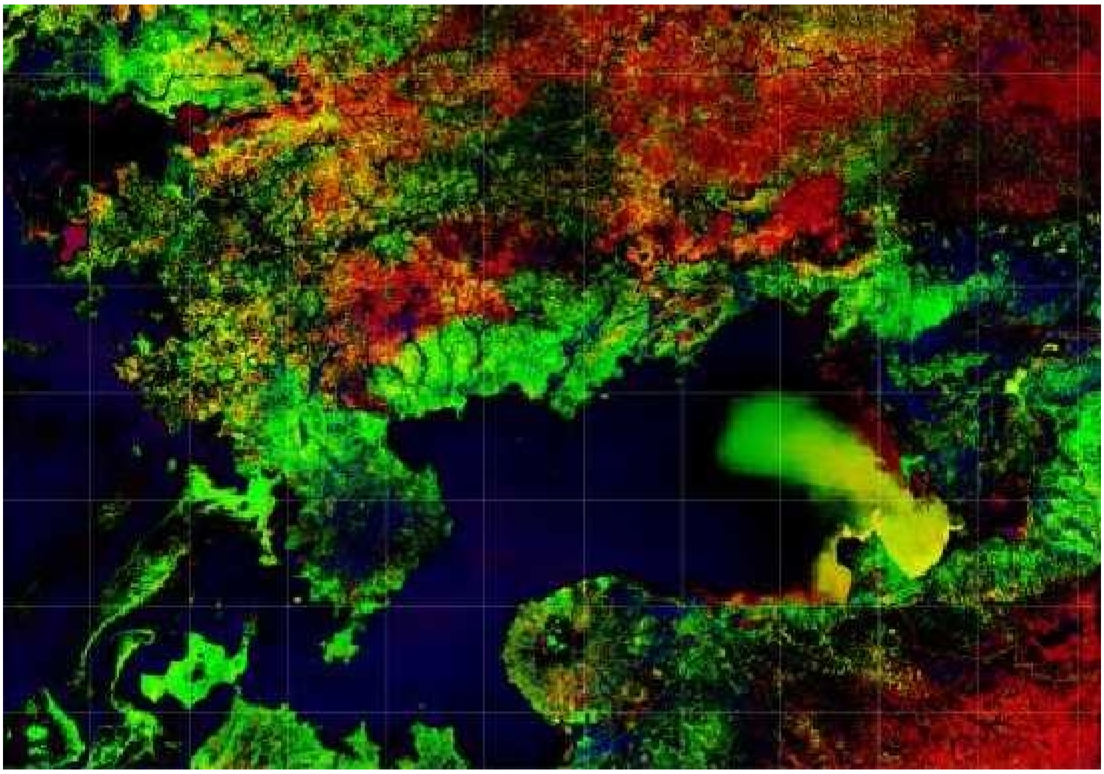

Fig. 4. Sediment plume originating from the outlet of the River Nyando in the Winam Gulf area of Lake Victoria. Area of coverage is 12,480 km^2.

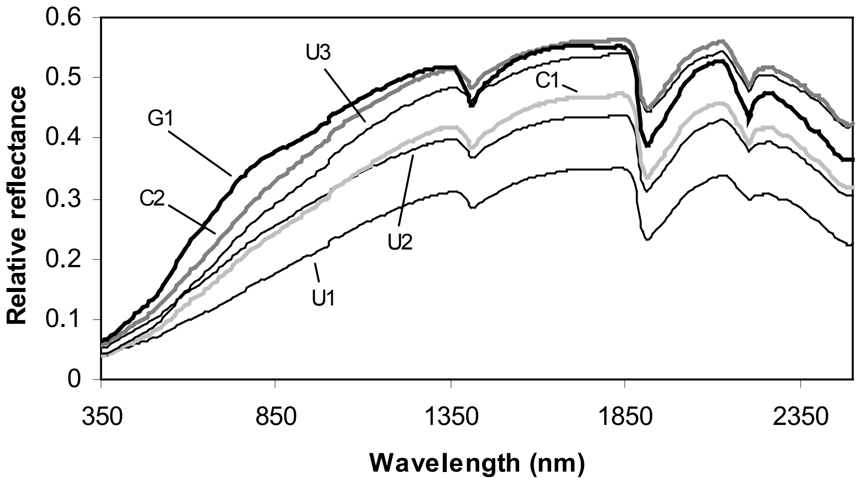

Fig. 5. Average reflectance spectra for six groups of alluvial soils from the Nyando River Basin in Western Kenya. Soils were sorted into groups using CART© classification (*25*) on the basis of visible signs of accelerated soil degradation observed during field survey and soil reflectance. The soil groups are non-eroded (U1, U2, U3), capped (C1, C2), and gully-edge (G1).

Table 4: Partial soil degradation risk profiles for six major groups of alluvial soils from Kenyan portion of the Victoria Lake Basin. The soil groups are non-eroded (U1, U2, U3), capped (C1, C2), and gully-edge (G1). The risk profile variables are: *prob* (C) = posterior probability of being sampled from capped site; *prob* (G) = posterior probability of being sampled from gully-edge sites.

Soil Group	n	*prob* (C)	*prob* (G)
U1	85	0.06	0.02
U2	66	0.18	0.02
U3	52	0.04	0.06
C1	46	0.57	0.24
C2	32	0.41	0.22
G1	43	0.26	0.63

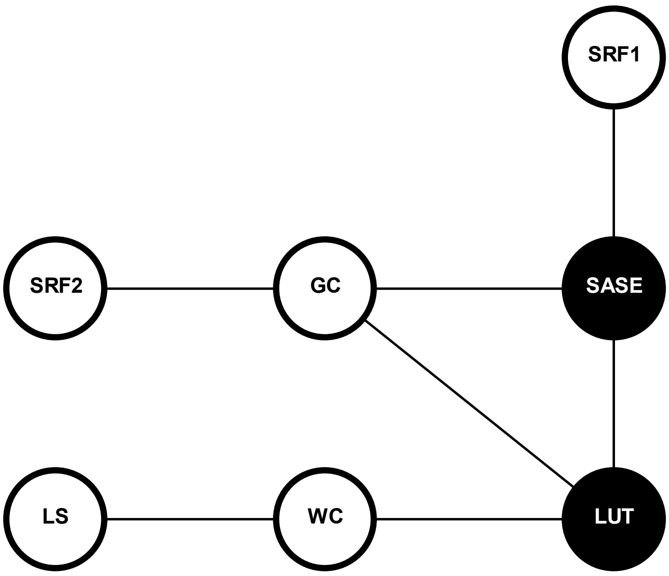

Fig. 6. Graphical model showing modeled conditional dependencies between visible signs of accelerated soil erosion, ground observations and soil reflectance. Signs of accelerated soil erosion (SASE is a categorical variable in 2 classes 1 = no visible signs of accelerated soil erosion, 2 = sites w. rills, gullies or capped soils); land use type (LUT is a categorical variable in 3 classes, 1 = smallholder agriculture, 2 = commercial agriculture, 3 = other land uses incl. forest, rangeland & wetland categories); ground vegetation cover (GC in % cover to 1 m height), woody vegetation cover (WC in % basal cover) slope LS-factor (*24*) and soil reflectance (SRF1 & SRF2 = 1^{rst} two principle components of soil reflectance, SRF1 accounts for 94% and SRF2 for 5% of the variation in soil reflectance across all sampled 30$\times$30 meter plots (n = 150)). All depicted conditional dependencies are significant at the $p < 0.01$ level.

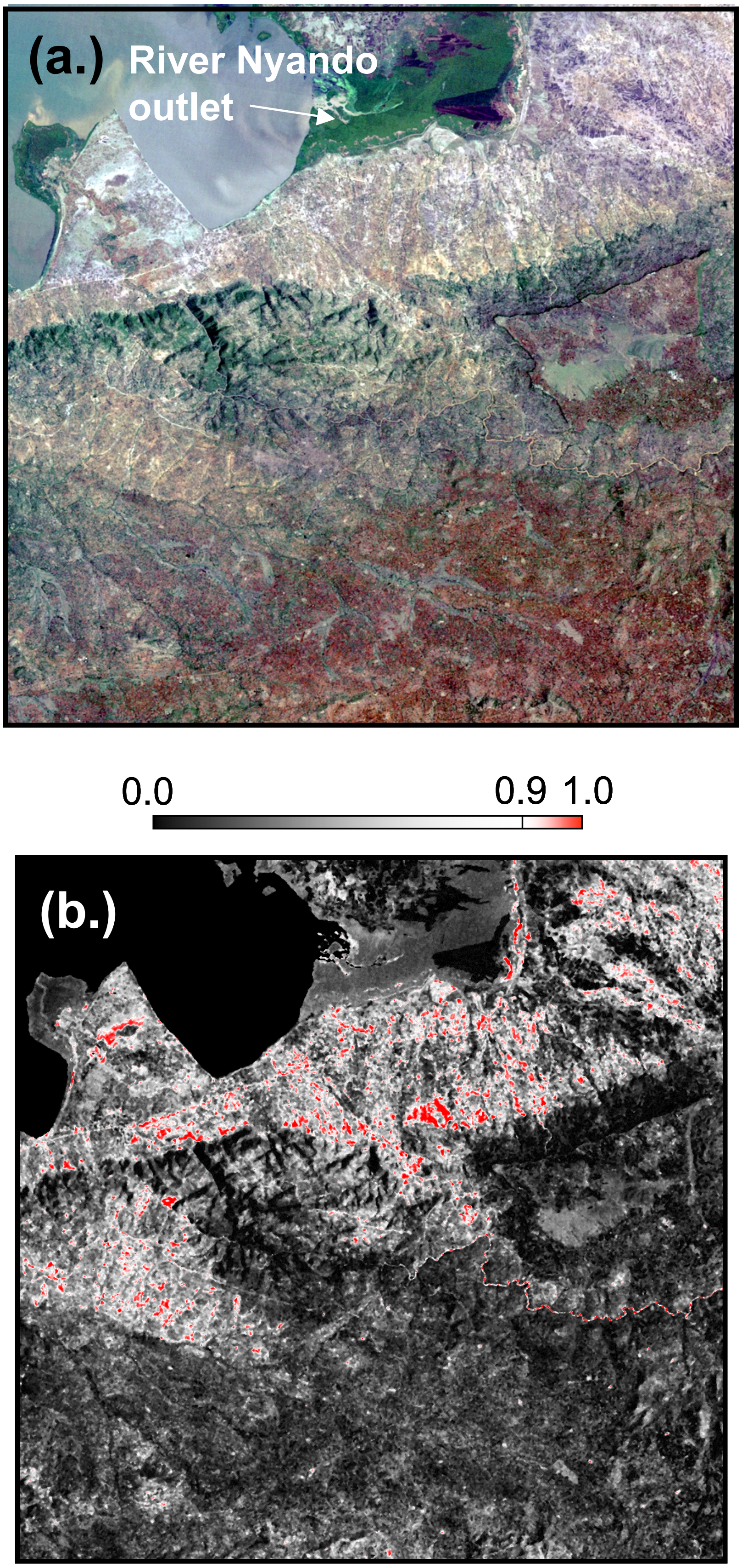

Fig. 7. Targeting potential soil erosion hotspots in landscapes. (a.) Near true color Landsat 5 composite of an area covering the outlet of the River Nyando in Western Kenya. Area of coverage is 729 km^2 (b.) Conditional probability matching of areas corresponding to sites with rills, gullies or capped soils.

7. Implications for Remote Sensing of Soil Quality

We have demonstrated the operational feasibility of using DRS as an integrated indicator of both long- as well as short-term variations in soil quality for plant production. We have also demonstrated how DRS can be used for calibration of landscape models relating soil properties, such as proneness to soil erosion, to Landsat 5 imagery. Because it was possible to distinguish different erosion surface types in this study, we believe that it may be possible to directly calibrate DRS measurements to dynamic tests of soil erodibility such as those using run-off plots (*27*) and rainfall simulators (*28*) that are typically very expensive and time consuming to implement under field conditions. We are further testing the use of DRS to help locate sources of suspended or deposited sediments in rivers, lakes and wetlands by matching spectral signatures of the sediments with those from spectral libraries of soils within a catchment.

In the laboratory, DRS requires only minimally processed soils and a single operator can run several hundred samples a day. If required, the process could easily be fully automated for continuous or batch processing. There are also good prospects for rapid characterization of soil quality in the field using currently available portable spectrometers, with or without artificial light sources. The current cost of portable instruments is about $60,000, but limited wavelength range instruments are available for around $10,000, and costs are expected to decrease as technology advances. Standard soil tests costs are in the range US$10–100 per sample and analysis. We have shown that even Landsat 5 simulated spectra are useful for soil quality characterization under conditions of local calibration, which will facilitate the use of cheaper field instrumentation, natural light sources and aircraft and space applications. Until further advances are made in methods for unmixing soil background signal from vegetation and other materials, we suggest that laboratory and field-based DRS, used in conjunction with field observations and satellite imagery as shown here, may provide a promising technique for assessing spatial distribution in soil properties, such as soil carbon stocks, over large extents.

These advances have major implications for how we conduct experiments, and surveys of the impacts of interventions on soil quality and productivity. For example, through rapid characterization of spatial variation in soil quality, DRS could help to improve experimental and survey design and analysis, and provide cheaper and more rapid farm advisory services. The ability to collect real-time data on soil quality and its response to management at high levels of spatial resolution should greatly enhance adaptive management of natural resources, including precision agriculture and watershed management. An integrated soil quality index can also be an important tool in economic analysis of agricultural systems (*29*).

Because DRS correlated well with a range of basic soil properties, there is good reason to expect that it will also predict a number of related soil ecological and engineering functions, such as anion and cation retention, and site stability. Furthermore, it may be possible to use DRS to assess traditionally 'difficult' soil functions, such as soil carbon sequestration potential, buffering effects of soil microbial processes on pollution (*30*) and soil factors related to plant community succession-retrogression. We envisage that the direct calibration of different soil functions to soil reflectance at multiple levels of observation will replace much current soil management research that is site specific. Countries in tropical regions where resources for land resource surveys, soils research and soil analyses are most severely limited may benefit most from these advances.

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12. The treatments were with or without the addition of mineral fertilizers (120 kg N and 52 kg P ha^{-1} yr^{-1}), application of cattle manure (10 t ha^{-1} yr^{-1}) and retention of maize stover, arranged as a 2 x 2 x 2 factorial design. Soil was collected after 17 years of cropping. The experimental details are described in J. J. Kapkiyai, N. K. Karanja, J. N. Qureshi, P. C. Smithson, P. L. Woomer, *Soil Biol. Biochem*. **31**, 1773 (1999).

13. The land-use systems involved growth of a one season maize crop after 17 months of either (i) *Sesbania sesban* (L.) Merr. tree growth, (ii) natural regrowth of vegetation without cultivation, (iii) three crops of unfertilized maize, or (iv) bare uncultivated soil. The experimental details are described in J. B. Maroko, R. J. Buresh, P. C. Smithson, *Soil Sci. Soc. Am. J.* **63**, 320 (1999).

14. The land-use systems involved growth of a maize crop after two years of either (i) *Sesbania sesban* (L.) Merr. tree growth, (ii) *Tephrosia vogelli* Hook. f. tree growth, (iii) natural regrowth of vegetation without cultivation, or (iv) two crops of unfertilized maize. The experiment is described in H. van Houten, Ed., *ICRAF Annual Report 1994*. (International Centre for Research in Agroforestry, Nairobi, Kenya), pp. 142-146.

15. Soils were sampled to a depth of 20 cm within the lower catchments of Nyando and Sondu rivers in Western Kenya.

16. Manufactured by Analytical Spectral Devices Inc, Boulder, Colorado, USA.

17. Soils 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

30° zenital angle and at a distance of 50 cm from the sample. Reflected light was collected with a 25° field-of-view foreoptic at a distance of 5 cm from the sample, at a 30° zenital angle and perpendicular to the plane of illumination. Soil samples 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 90°. Ten spectra were recorded at each position and averaged. Before reading each sample ten white reference spectra were recorded using calibrated spectralon (Labsphere®) 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 are about 1% among rotations within a sample dish, and 2% for replicate dishes from a soil sample.

18. Produced by Research Systems Inc, Boulder, Colorado, USA.

19. D. Edwards, *Introduction to Graphical Modelling* (Springer-Verlag, New York, USA, 1995).

20. Because soils were sampled immediately after incorporation of fallow biomass, litter decomposition is likely to have been incomplete. Better fits would be expected if soils were sampled after the incorporated biomass had decomposed.

21. J. Neter, W. Wasserman, M. Kutner, *Applied Linear Statistical Models* (Erwin, Homewood, Illinois, ed. 2, 1985).

22. The primary purpose of this ongoing study is to guide on-ground remediation efforts by Kenyan land management agencies that are responsible for non-point source pollution control in the Kenyan portion of the Lake Victoria Basin (ca. 38,000 km^2).

23. The image was derived from Spectral Angle Mapper unmixing of a Landsat 5 image, as described by F. A. Kruse et al., *Remote Sens. Environ*. **44**, 145 (1993), using soil reflectance spectra collected during ground survey. The image was calibrated using pseudo-invariant targets as described by J. R. Schott, C. Salvaggio, W. J. Volchok, *Remote Sens. Environ*. **26**, 1(1988).

24. Ground sampling followed a spatially stratified design, whereby at least 50 30 × 30 m plots were sampled per 15 minute quadrangle (app. 27 × 27 km blocks). Blocks were further stratified into 500 × 500 m focal areas using available geological maps, satellite images and digital elevation models to capture major variations in parent materials and

land cover types. Focal areas were then sampled either in the direction of the dominant physiographic gradient (upland to bottomland), or in the case of flat terrain, on the basis of the dominant land use types in the area. All plot locations were georeferenced using survey grade GPS. For each plot detailed observations of slope characteristics, vegetation cover and composition, land use and signs of accelerated soil erosion were recorded and field spectra of rocks, soils, and vegetation were obtained. Top- and sub-soils were collected from 3 equally spaced locations along the center-line of each plot.

25. L. Brieman, J. Friedman, R. Olshen, C. Stone, *Classification and Regression Trees*. (Pacific Grove, Wadsworth, 1984)

26. The model used to derive Fig. 7 was essentially equivalent to that shown in Fig. 6 but pixel reflectance values (bands 1,2,3,4,5 & 7) were extracted from a Landsat 5 scene and added to the model. Linear combinations of bands 1,4,5, & 7 were then used to discriminate between sites where we observed no visible signs of accelerated soil erosion, and those that were either capped or near gully edges.

27. W. H. Wischmeier and D. D. Smith, *Agric. Handb. No. 537* (USDA-SEA, Washington, D.C., 1978).

28. R. Woodburn and J. Kozachyn, *Trans. Amer. Geophys. Union* 37, 749 (1956).

29. E. C. Jaenicke and L. L. Lengnick, *Amer. J. Agr. Econ*. **81**, 881 (1999).

30. C. Palmborg and A. Nordgren, *Soil Biol. Biochem.* **28**, 711 (1996).

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