SOIL OPTICAL PROPERTIES AND ENVIRONMENTAL APPLICATIONS OF REMOTE SENSING

Richard Escadafal, ORSTOM, Bondy, France
and
Alfredo R. Huete, University of Arizona, Tucson, USA

ABSTRACT:

Soil spectral properties in the optical domain are related to soil minerals and organic compounds, water content, and soil particle size and structure. On the one hand, the understanding of these relationships is the basis for high resolution remote sensing studies of soil biophysical properties.

On the other hand, soil spectral and spatial variability create a noisy background signal hampering the quantitative assessment of vegetation in mixed, soil-plant canopies.

In this paper, we review soil spectral signatures and summarize techniques usable both for soil signal enhancement and for soil noise removal for vegetation studies. Both are deemed necessary in terrestrial studies of desertification processes, productivity studies, and environmental change studies involving optical remote sensing.

KEY WORDS: soils, optical properties, soil composition, improvement of vegetation indices.

1. INTRODUCTION

The development of environmental applications of optical remote sensing has been largely based on intensive studies of rocks and vegetation spectral properties. Numerous laboratory studies have been performed to characterize the features of a large variety of minerals, building the basis for multispectral remote sensing of geological structures and ore deposits (Hunt, 1977; Clark et al, 1990).

As vegetation assessment and monitoring is a fundamental issue in environmental remote sensing, many studies have been aimed at measuring the plant spectral properties. Only a limited number of studies, however, have been devoted to the assessment of soil optical properties. This is partly due to the general opinion that soils are nothing but altered rocks, a relatively neutral background, largely masked by the vegetation. However, soils are a major component of the Earth surface observed by remote sensing. Over large parts of terrestrial environments soils are temporarily exposed (deforestation, plowing,...), or permanently (deserts and arid zones). The importance of considering soils in remote sensing of terrestrial ecosystems has been recently emphasized (e.g. GRAETZ, 1990). In this perspective, we will try to give a few trends on the contribution of soils in current and future optical remote sensing of the environment.

2. SOIL OPTICAL PROPERTIES

2.1 Technique: Measuring Soil Spectra

Current laboratory instruments such as spectrophotometers can be straightforwardly used for soil spectral reflectance measurements. Soil samples are more readily prepared for scanning with a spectrophotometer than rocks or plant samples. After air-drying, a simple sieving is generally sufficient for a first run. A more rigorous approach requires grinding of the soil sample down to a standard grain size. The optical quality of the sample holder needs also to be carefully checked. An overview of the application of the spectrophotometric technique to obtain soil spectral reflectance curves can be found in Bedidi et al. (1992).

In the field, spectral data can also be easily recorded over soils with hand-held devices, whereas measurement of canopies often require more complex attachments such as cherry picker booms or truck mounted cranes. By ratioing the radiances observed over soils by the one measured over a reference target (compressed halon plate for instance) reflectance factors can be computed.

The recent advent of new type of portable instrument has brought field spectra measurements to a new era (Satterwhite and Henley, 1987). After the generation of broad band instruments such as portable radiometers, array detector technology and high density computer storage of data has allowed the development of portable spectrometers. They currently perform very satisfactorily in the visible to near-infrared range. Newer mid-infrared detectors will allow for coverage of the full optical domain in the near future. Technically, laboratory spectrophotometers measure the diffuse reflectance (they use an integrating sphere) while field instruments measure bidirectional reflectance factors which vary with the geometry of the sun-target system. In the case of soils, this latter effect is obviously more pronounced for soils with rough surfaces. Although these geometrical conditions affect the apparent brightness of the soils, the spectral shape remain almost constant (Escadafal and Huete, 1991a). Thus, field recorded reflectance factor curves retain the spectral features and can be compared to laboratory spectra of pure minerals, for instance.

2.2 General Trends of Soil Spectra

An overview of the main types of soil spectra is made possible through two sets of laboratory measurements from a series of various soils samples from the United States (and Brazil). The first series has been studied by Condit (1970) who gave a statistical analysis for the set of spectrophotometric measures in the 400-1100 nm range. Soils were observed in dry and wet conditions, but little is known about the soil preparation and the sample holder used, and the original spectra were not published.

More recently, Baumgardner et al. studied a large series of soil samples with a spectroradiometer and a stabilized light source. The covered spectral range goes up to 2400 nm, but the illumination was not diffuse and the samples were wetted for 'uniformization'. Given these non-standard conditions, this series cannot be used as a reference, although it has been successfully used for determining the main broad types of soil curves (Baumgardner et al., 1985) and soil data dimensionality (Price, 1990).

Figure 1 illustrates different soil spectral curve types frequently observed in the visible-NIR range. These spectra were obtained using a field spectroradiometer over a series of soil samples of various composition (see Huete and Escadafal, 1991, 1992 for details). The characteristics of the soils cited as examples in this paper are reported in Table 1.

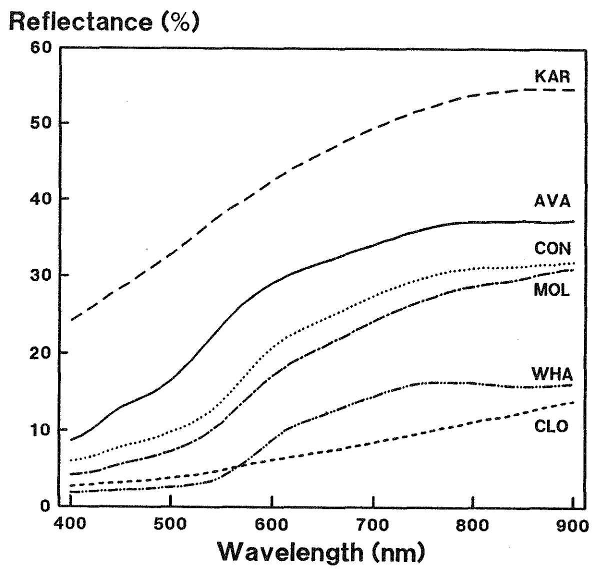

Fig. 1. Example of soil reflectance spectra recorded with a portable field spectroradiometer (after Huete and Escadafal, 1991. See Table 1 for soil characteristics).

The first striking feature is that soil spectra vary mainly in brightness. This observation led to the concept of the 'soil line' discussed below, and to the opinion that albedo is the main property of soils when considering their role in the biosphere (particularly in global models, Wilson and Henderson-Sellers, 1987).

The general variation in shape has been fairly well described by Condit (1970). Soils have a reflectance regularly increasing with wavelength forming a convex curve in the general case (soil KARro on Figure 1). A second type can be described as sigmoidal (AVA, CONtine, MOLokai), whereas dark organic soil spectra have a convex shape (CLOverspring). These spectral features are related to soil composition.

2.3 Soil Spectra and Soil Components

2.3.1 Soil Mineralogy As soils are mainly composed of mineral grains of various sizes, the spectral features recognized in those common minerals are very often observed in soils. Absorption bands of carbonates, sulfates and clay minerals have been described in the literature (Clark et al, 1990), they mainly occur in the mid-infrared part of the spectrum. Interpretation of these features is well developed in geologic remote sensing (i.e. with Landsat TM data) and can be easily applied to soil mineralogy assessment (Mulders, 1987).

From this respect, it is worth mentioning that soils are rather intensively homogenized by the natural fauna and/or human activity so that their surface often reflect the inner composition of soils, contrary to exposed rocks whose patina or surficial alterations may present very different minerals.

2.3.2 Iron Oxides Iron oxides are alteration products very common in soils. These minerals are usually present in limited amounts, but they play an important role as they reflect the type and the degree of evolution of the soil (pedogenesis). Two main iron oxides are responsible of soil color, hematite, giving a red color and goethite giving a yellowish color. Color, a criteria widely used in soil classification, is the visual manifestation of an absorption. On Figure 2 the curves of iron affected soils all show a similar sigmoidal shape due to the absorption in the shorter wavelengths.

Iron-rich soils (CORnutt and MOLokai), show a red color (see Table 1) and a typical hematite curve shape, with the

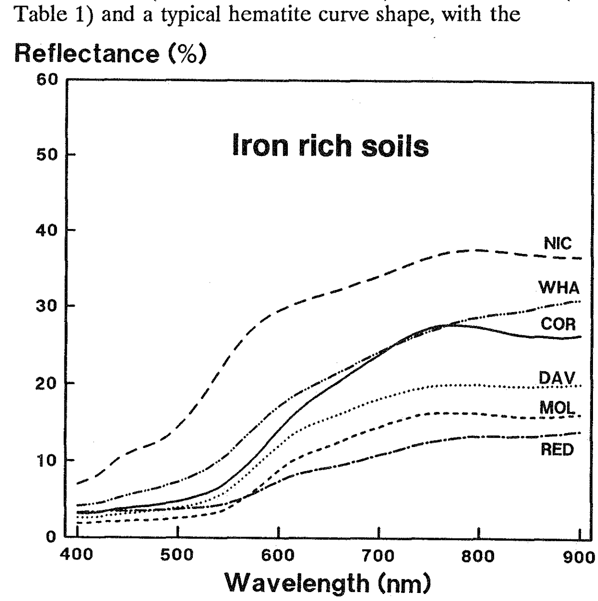

Fig. 2. Example of spectra of iron oxide rich soils (see Table 1 for soil characteristics).

Table 1. Characteristics of the soil samples used in this study

Symbol	Series	Soil Taxonomy	Munsell Color(*)	%Clay	%Sand	%Fe	%Carb
AVA	Ava	mesic typic fragiudalf	5.1 YR 6.0/4.0	31	9	1.25	0.880
CLO	Cloversprings	cumulic cryoborolls	4.5 YR 2.7/1.5	21	40	2.00	0.930
COM	Comoro	thermic typic torrifluvent	4.9 YR 3.6/1.9	5	84	1.60	0.240
CON	Contine	hyperthermic typic haplargids	3.8 YR 4.5/3.7	26	52	0.70	0.970
COR	Cornutt	mesic ultic haloxeralfs				24.80	0.005
DAV	Davidson	thermic rhodic kandiudults	2.9 YR 3.3/4.2	52	25	10.20	0.580
HOL	Holtville	hyperthermic typic torrifluvent	4.4 YR 4.4/2.1	41	9	0.90	0.380
KAR	Karro	thermic ustollic calciorthids	9.9 YR 6.9/2.3			0.19	1.198
LAV	Laveen	hyperthermic typic calciorthids	4.1 YR 4.7/3.0	19	46	0.80	0.005
MOH	Mohave	thermic typic haplargids	3.8 YR 4.8/3.6	23	59	0.60	0.630
MOL	Molokai	isohyperthermic typic torrox	2.2 YR 2.7/4.0	52	23	12.50	0.740
NIC	Nicholson	mesic typic fragiudalf	5.2 YR 5.5/4.0	49	4	2.80	0.005
PIN	Pinaleno	thermic typic haplargids	4.2 YR 4.7/3.4	7	71	0.90	0.890
RED	Red Cinders		1.4 YR 3.1/2.7			2.25	0.110
SUP	Superstition	hyperthermic typic calciorthids	4.6 YR 5.7/3.1	2	96	0.47	0.300
VIN	Vint	hyperthermic typic torrifluvent	4.3 YR 4.9/2.9	4	82	0.80	0.840
WHA	White house	thermic ustollic haplargids	3.9 YR 4.1/4.0	7	79	1.50	0.890
YUM	Yuma		4.8 YR 5.5/3.1	30	2	0.90	1.000

(*) Munsell color computed from reflectance spectra (see Escadafal et al., 1989 for details on technique) absorption extending to the 550 nm region. The yellowish NICholson soil has a more goethite shaped curve absorbing mainly in the blue band region. In fact most of the soils show intermediate shapes as they are mixtures of skeletal minerals (such as quartz, calcium carbonate), iron oxi-hydroxides, and organic matter. The 'coloring efficiency' or the spectral effect of these different compounds vary greatly with their grain size and organization. For instance very low amounts of hematite in the form of coatings on quartz grains can produce a very vivid red color resulting in a spectrum similar to hematite. The White House A soil shows a typical 'mixed' signature of iron affected soil darkened by organic matter.

2.3.3 Organic Matter It is well known that the general effect of organic matter is the darkening of the soil. A more detailed analysis also shows a modification of the spectrum shape whereby soils rich in organic carbon have a very low reflectance with a concave curve (soils COMoro and CLOverspring on Figure 3). However, this feature is rather subtle and vanishes at lower organic contents (HOLtville, GRAbe and YUMa soils). It is then difficult to assess the organic content of a soil from its spectral curve.

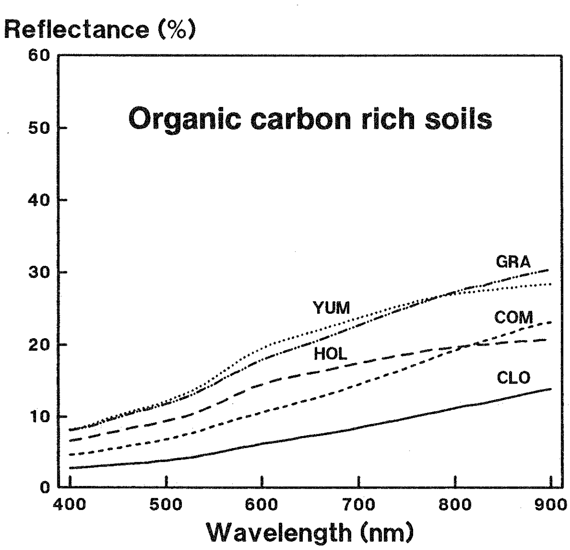

Fig. 3. Example of spectra of organic carbon rich soils (see Table 1 for soil characteristics).

2.3.4 Water Content Water is present in soil minerals (such as gypsum in some arid soils) but soil water is mainly adsorbed at the surface of the grains and in the portal space. The quantity of water is highly variable but is of great interest as it conditions biomass production in general. Water related absorption bands present in the mid-infrared can be partly accessed with Landsat TM for soil humidity estimation (Musick and Pelletier, 1988). In the visible, the overall effect of water is a rather homothetic decrease in reflectance. However, in a recent study concerning oxisols from Brazil, Bedidi et al. (1992) showed that the spectral shape of those colored soils (i.e. with marked absorption features in the visible) is modified by the water content level.

3. REMOTE SENSING OF SOIL TYPE AND COMPOSITION

3.1 Soil Spectral Discrimination

From the previous discussion it can be summarized that brightness is the most dominant optical soil parameter, being simultaneously affected by the viewing geometry, the surface roughness, the organic matter and water contents. It is then generally difficult to retrieve any of these parameters from remotely sensed soil albedo. On the contrary, we have seen that the spectral curve shape is more specifically related to certain variables and less sensitive to geometrical conditions.

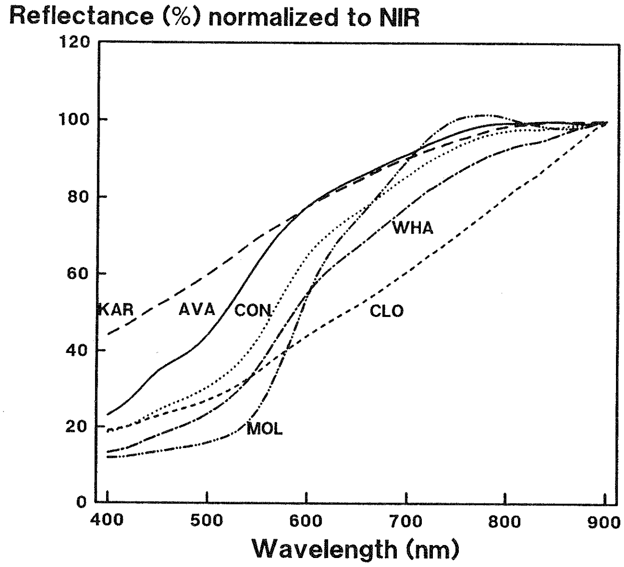

Fig. 4. Visible-NIR reflectance variability among soils (soil spectra of Figure 1 are normalized to 900 nm to facilitate intercomparison of spectral shapes).

In Figure 4 the brightness information has been removed by normalizing the soil spectra of Figure 1 to the NIR reflectance (assuming 100% at 900 nm). The differences among soils appear more clearly and show that the soil spectral signatures vary significantly. This variability has been used for soil discrimination in multispectral classification of satellite imagery for soil mapping. The spectral features occurring in the visible domain are responsible for color variations. In the Munsell Color system, widely used in Soil Science, hue (related to the overall shape) and chroma (related to the intensity of the absorption features) describe the spectral signature, whereas value varies with the brightness. Retrieving color information from remote sensing data is then a useful technique for soil surveying and monitoring (Escadafal, 1989; Escadafal et al., 1989; Curran et al., 1990).

3.2 Towards a Quantitative Approach

Our studies have shown that because of the relatively simple shape of soil spectra, color can be quantitatively related to soil spectral reflectance. Simple models have been derived from this approach to assess color from satellite data (i.e., Landsat Thematic Mapper), based on the conversion of Munsell color into R,G,B coordinates (Escadafal, 1992).

The soil composition is more difficult to assess. It is possible to come up with qualitative information such as 'iron affected' or 'rich in organic carbon', but the quantitative approach is more difficult. The coming age of continuous spectrum remote sensing with imaging spectroradiometers will allow more sophisticated data processing such as derivative spectrometry techniques, enhancing spectral differences as shown on Figure 5.

Currently however, in specific situations such as a certain soil type in a limited geographic area, quantitative relationships have been established. As an example, combining the quantitative relationships established by Torrent et al. (1983) between color and hematite content and the model for remote sensing of color with Landsat TM mentioned above, Madeira recently proposed a Landsat TM band combination for remote sensing of the hematite content of oxisols from Brazil (Madeira, 1992).

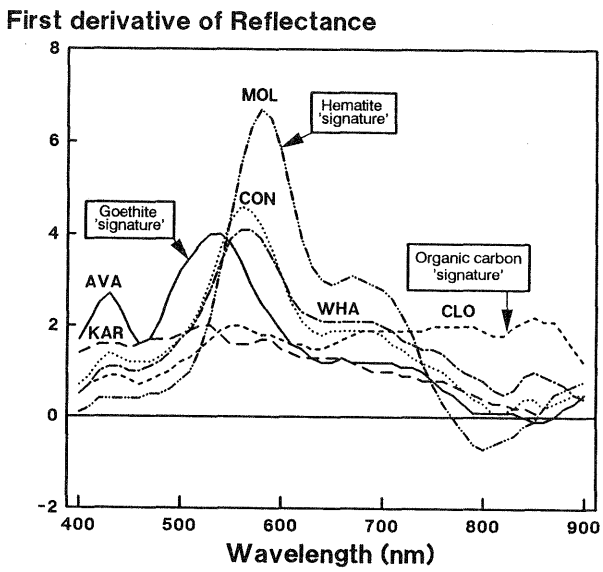

Fig 5. First derivatives of oil spectra series of Figure 1.

Other more geographically limited examples can be found in the literature such as relating soil brightness to organic carbon content at a farm level. Unfortunately, these local empirical correlations cannot be used for more global remote sensing of soil carbon content.

As stressed above, the spectral influence of a given amount of a given soil component varies tremendously with the particle size and the distribution in the soil. These characteristics are largely related to the soil forming processes and history, or the soil class and type. As a consequence, today there is no general model relating the optical properties of soils to their composition.

4. SOIL SPECTRAL NOISE IN REMOTE SENSING OF VEGETATION

4.1 Evidence of Soil Noise

Interest in soil optical characteristics comes not only from the possibility of assessing soil types and soil properties from space, even if this is in itself an important aspect of remote sensing of environment.

While working at refining the indices and models used in optical remote sensing of vegetation, several researchers found that soils have an influence on the spectral behavior of plant canopies, particularly when they are incomplete (Ezra et al., 1984; Heilman and Boyd, 1986; Huete, 1987). Recently, Huete and Tucker (1991) found numerous soil artifacts in NDVI values derived from NOAA-AVHRR data over the Sahara. These alterations of the vegetation signal by the soil will be discusssed here under the name of 'soil noise'.

4.2 Causes of Soil Noise

4.2.1 Soil Type Influence In most of the indices developed for remote sensing of vegetation it is recognized that the infrared/red ratio varies essentially with green vegetation related parameters, such as density, biomass or percent cover. Atmospheric effects can also alter this ratio, but these effects are not a feature limited to soils and vegetation and they are largely discussed in the literature. Here we will limit our discussion to ground-based optical properties.

The concept of vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) implies that soils have a constant infrared(IR)/red(R) ratio whereas their brightness can vary largely, describing a soil line in the infrared/red reflectance data plane.

$$NDVI = (IR-R)/(IR+R) \qquad (1)$$

While looking at Figure 4 it is obvious that this assumption is not always true. When compared to the infrared, red reflectance values vary largely among soils. As a result, without the presence of any vegetation some soils will have higher NDVI values than others, producing a 'noise' in the vegetation index. This is what is observed in Figure 6 where NDVI values have been computed for four different sensors from a series of spectra recorded over bare soils.

Noticeably, this noise is related to the two peculiar curve shapes: the sigmoidal curve of iron rich soils and the concave curve of organic soils. In the latter case the noise intensity is particularly enhanced by the fact that the overall reflectance is low. At those low values a slight modification of the IR value will lead to a strong NDVI change.

4.2.2 Sensor Band Width Effect Remote sensing satellite sensors operating in the spectral range considered here have different band specifications. For a given soil the 'red' and 'infrared' signals vary with the corresponding band spectral windows. For instance, because of broader spectral bands encompassing shorter wavelengths, AVHRR has the highest NDVI fluctuations over the studied soil series, while SPOT XS with narrower spectral bands has the smallest (Figure 6).

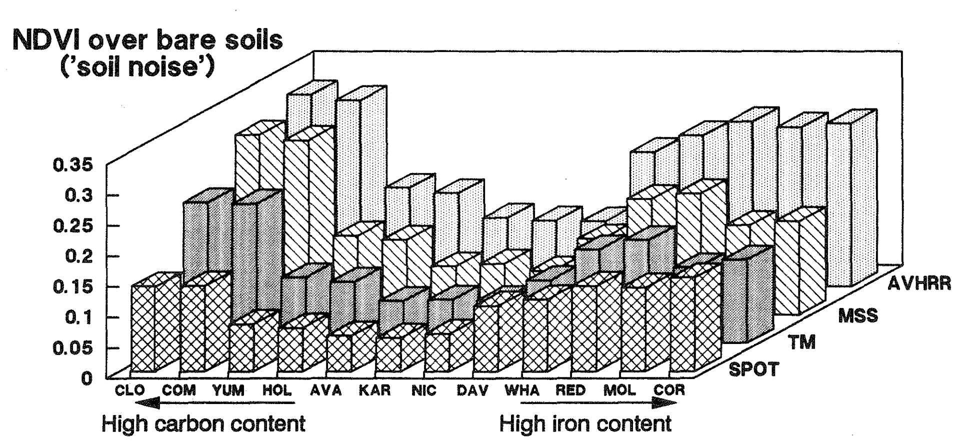

Fig. 6. NDVI values for four different sensors (AVHRR, Landsat MSS, Landsat TM and Spot XS) simulated from spectroradiometric data of different types of soils (see Table 1 for soil characteristics).

Although these field data derived values do not take into account the atmospheric attenuation observed in real AVHRR imagery, it should be noticed that the 'noise' level observed here is far from totally negligible.

4.3 Remedies

Different techniques can be imagined to take the soil spectral variability into account when designing vegetation indices. The link between the soil spectral shape and the noise is obvious, but two different situations must be distinguished. In the case of organic soils, the noise is rapidly increasing with the concavity of the curve. When using vegetation indices where the origin of the soil line is shifted such as the SAVI (Huete, 1988) the noise of organic soils is diminished. For iron rich soils the noise is linked to the sigmoidal aspect of the curve, and another correction method can be designed.

4.3.1 Experiment with Aridic Soils The case of aridic soils is interesting as their organic content is very low, they are often colored by iron oxides, and they are the dominant spectral component of arid environments observed from space, i.e. more likely to be a source of noise in vegetation indices.

Based on simulated TM data obtained from spectra recorded over ten aridic soils, a simple noise correction technique has been recently proposed by Escadafal and Huete (1991b). The intensity of the absorption due to the iron oxides is related to a redness index, RI, combining the red and green bands (e.g. TM bands 3 and 2) in a manner similar to the NDVI:

$$RI = (R-G)/(R+G) \qquad (2)$$

This index varies with the slope of the steep part of the soil spectral curves. It was found to be significantly correlated with the NDVI values computed for the same studied soils, that is to say with the noise intensity.

$$RI = k \cdot NDVI \text{ , with } r2 = 0.72 \qquad (3)$$

The actual vegetation signal in the NDVI can then be computed by removing this soil induced signal from the raw NDVI values, giving a corrected index, NDVI*.

$$NDVI^* = NDVI - k \cdot RI \qquad (4)$$

Although the SAVI in itself already dampens the soil noise comparatively to the NDVI, a noise corrected SAVI was similarly tested (k was equal to 0.45 for the NDVI and to 0.27 for the SAVI).

Figure 7 shows the dispersion of the raw NDVI and SAVI values obtained from the data over the ten studied soils, compared with the dispersion after noise correction. For both indices, the noise amplitude is reduced by about a factor of 2, which indicates a doubling of the vegetation index sensitivity to low vegetation amounts.

4.3.2 Application to Satellite Derived NDVI Imagery These first interesting results are currently tested with different types of satellite imagery over vegetated areas with low vegetation cover. The application to Spot or Landsat multispectral data is rather straightforward, assuming atmospheric corrections can be done properly, and 'pure soils pixels' can be found in the imagery to compute the coefficient k.

NOAA-AVHRR are the most intensively used data to monitor the vegetation changes over large areas. They are also the most affected by soil noise, notably because of the broadness of the bands of this sensor as discussed above. Unfortunately, this sensor provides no other visible band to take the soil spectral shape into account for soil noise correction purposes.

However, in an experiment reported in a forthcoming paper (Escadafal et al., 1992) we have merged an AVHRR-LAC image with a CZCS image acquired over Northern Africa. We have shown that the soil artifacts and noise observed in AVHRR derived NDVI data can be corrected using the CZCS blue and red bands to compute a redness index as described above.

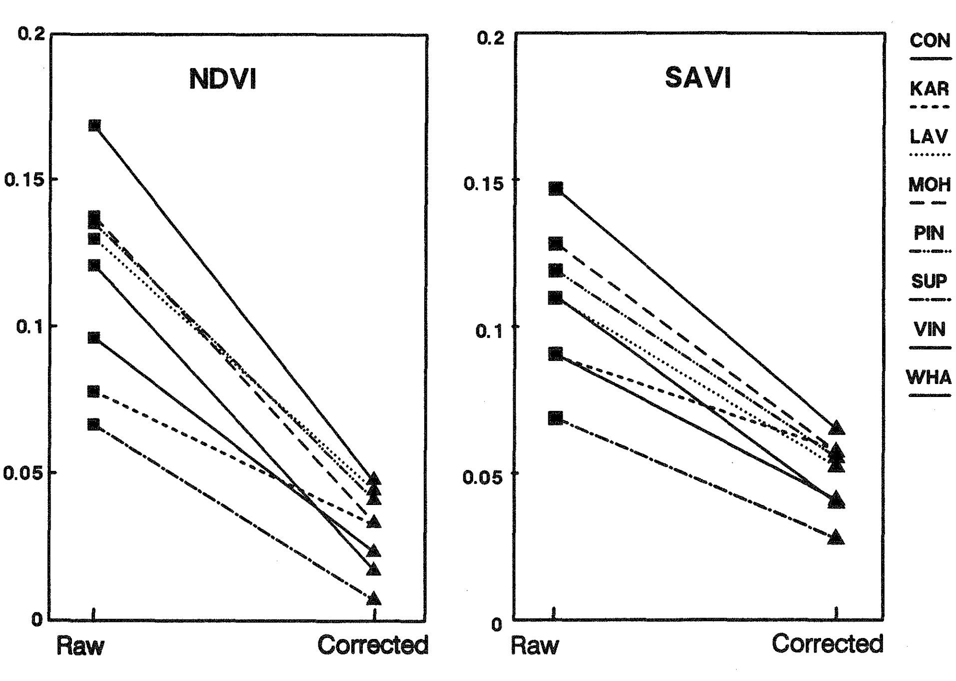

Fig. 7. Soil noise correction in vegetation indices: NDVI and SAVI values computed for ten acidic soils of Arizona raw: without correction corrected: after noise reduction using the 'redness index', see text. (see Table 1 for soil characteristics).

The current applicability of this last result is limited because NOAA-CZCS is no longer functioning, but it might be a good test of the next generation of medium resolution remote sensing data such as from the NASA-MODIS (Salomonson et al., 1990) or SPOT-Vegetation, which will have several visible bands.

5. CONCLUSION-PERSPECTIVE: SOILS ARE NOT A GREY BACKGROUND!

Under the current technology of optical remote sensing, soils cannot anymore be considered a neutral background. Besides their strong -OH bearing mineral features in the mid-infrared, they show important variations of their spectral shapes in the visible-NIR range. In the near future, new instruments with more bands in this domain (Vane and Goetz, 1988) will allow a better assessment of soil spectral shapes and hence of soil type and composition. Monitoring of soil surficial changes, of water and organic content, of erosion and desertification will be facilitated with polar orbiting platforms. The better depicted soil spectral variability will have to be taken into account more than ever when trying to retrieve data for non-soil components of mixed pixels.

Therefore, new processing techniques will have to be used for those high dimensional data sets, such as derivative spectroscopy and spectra unmixing (see Huete and Escadafal, 1991, for an example dealing with soils). A better knowledge of soil spectral properties will be needed, which means collecting more spectral measurements over soils and standardizing the techniques to establish a reference database and to facilitate intercomparisons.

Most of the current simple additive models assume that soils are an intimate mixture of different calibrated powders. A more realistic approach will have to be developed to modelize and predict the spectral behavior of soil from known properties such as soil data available in maps or databases. As an example, a model for estimating soil spectra from color has been recently tested (Escadafal et al., 1990). Independent assessment or estimation of soil optical properties will be useful for vegetation parameter unmixing. Moreover, it might also be a solution to overcome the high variability of soil reflectance in the blue band, when using that band for adjusting atmospheric effects in vegetation indices such as the one developed by Kaufman and Tanre (1992).

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