ESTIMATING SOIL SPECTRAL PROPERTIES (VISIBLE AND NIR) FROM COLOR AND ROUGHNESS FIELD DATA *

Richard Escadafal**

ORSTOM
Bondy, France

Alfredo Huete and Donald Post

University of Arizona
Tucson, U.S.A.

ABSTRACT

A method is presented to infer bare soil spectral reflectance from soil color visually determined with Munsell Charts. This method is based on a recent laboratory study using colorimetric concepts.

Twenty three Arizona soil surface samples were used and two types of soil surface conditions were created: 'smooth' and 'rough'. Spectral properties were measured in natural sunlight with a field portable spectroradiometer in the 370 to 900 nm wavelength range. The relationships between the color converted in C.I.E. coordinates and the reflectance data were derived using multiple regression techniques. Spectra reconstructed solely from Munsell color data were compared with the spectra measured with the spectroradiometer. For rough samples the reflectance values of the reconstructed spectra were reduced proportionally by the shadow percentage.

Predicted spectra showed an average error of about ±2 %, with a maximum of approximately ±5 %. The greatest errors were found at the two extremes of the spectral range considered. Thus the technique developed here is effective in inferring soil spectral properties from simple terrain data and is particularly useful when "ground truth" measurements are not available.

* Presented at the Twenty-Third International Symposium on Remote Sensing of Environment, Bangkok, Thailand, April 18-25, 1990.

** Currently visiting scientist at the University of Arizona, Tucson, U.S.A.

INTRODUCTION

Among the Earth surface components remotely sensed by satellites, soils are dominant in most situations where vegetation cover is low, either because of cultural practices or for climatic reasons. In arid areas, the interpretation of satellite data requires an understanding of soil spectral properties (Tueller, 1987 ; Escadafal, 1989). Furthermore, spectral indices for evaluating vegetation characteristics in arid rangelands are very sensitive to soil type and color (Huete et al., 1987 ; Huete, 1988).

The ground spectral properties of arid land surfaces are not easy to obtain due to the difficulty of access and the lack of available radiometric equipment. Several methods have been developed for the description of vegetation and soil surfaces to aid in the interpretation of satellite-measured radiances (Cihlar et al., 1987 ; Pouget and Mulders, 1988 ; Escadafal, 1989). Among the surface parameters to take into account, roughness is the most obvious as it reduces the overall surface radiance (Spiridinov et al., 1971; Graetz and Gentle, 1982). But to our knowledge no attempt has been made to directly correlate ground-based description data with spectral reflectance.

A recent laboratory study using colorimetry concepts, shows that soil color is uniquely related to spectral reflectance in the visible domain (Escadafal et al., 1988). It also has been shown that soil color, usually noted using the Munsell system, is more easily related to reflectance when expressed in C.I.E. color coordinates (Escadafal et al., 1989). This color system defined by the 'Commission Internationale de l'Eclairage' is the fundamental basis of color science and is widely used in the industry (Wyszecki and Stiles, 1982). Since the 1950's, soil color data is routinely collected in the field by soil scientists using Munsell charts (Pendleton and Nickerson, 1951 ; Soil Survey Staff, 1975). Worldwide, it is a very common environmental data input, available in soil maps, reports and data bases.

Available high resolution remote sensing data encompasses mainly the visible - near infrared spectral range. An attempt is made here to extend previous results of estimating soil reflectance in this same spectral domain to easily available field data : Munsell color and surface roughness.

MATERIALS and EXPERIMENT

23 soil samples from Arizona with a wide range of composition and color were used (see Huete et al., 1984). The soil samples were air-dried and passed through a 2mm-sieve. They were placed inside a 15 cm x 15 cm x 1 cm plastic tray and levelled. One tray was used for each soil, and all trays were positionned outdoors on an horizontal stand at the Campbell Avenue Experimental Farm of the University of Arizona, Tucson.

Reflected solar radiation was measured with a portable Spectron Engineering model SE 590[1] field spectroradiometer, providing measures in 252 adjacent bands in the 370-1100 nm spectral range. The instrument was fastened to a vertical stand so that the viewing direction was at nadir and orthogonal to the soil surface. Reflected radiation was measured with a 6° field-of-view lens from a height of 42 cm above the soil. Two readings were obtained per soil, one with a smooth surface, the other with a rough surface artificially created with parallel 1-cm deep furrows spaced 3-cm apart. Black and white nadir view photographs were taken for each rough surface. The experiment was conducted 16 February 1990 between 1200 and 1330 MST during a totally cloud-free day.

Reflectances were calculated by ratioing the soil-reflected energy to that from a Spectralon[1] standard reference panel. The 252 channel data was then resampled to 10 nm wavelength intervals to simplify data handling and more accurately depict the spectral resolution of the sensor.

The color of each soil sample was visually determined in diffuse daylight by comparison with Munsell soil color charts (Munsell Color Company, 1975). The average hue, value and chroma visually estimated by 25 observers was used in this study (Post et al., 1989). Each observer assigned the nearest integer unit of hue, value and chroma to each soil sample. Hue names were translated into the following numerical scale : 10YR = 1, 2.5YR = 2, 5YR = 3, 7.5YR = 4, 10YR = 5, 2.5YR = 6 (table 1).

Table 1. Visually estimated color of the 23 soil samples series: average Munsell color and corresponding C.I.E. coordinates

	Soil name	Munsell color Hue	Value	Chroma	C.I.E. color coordinates X	Y	Z
1	Agua	4.9	5.4	2.8	0.2404	0.2357	0.1753
2	Ava	5.5	6.9	4.0	0.4177	0.4163	0.2717
3	Avondale	4.3	5.3	3.9	0.2387	0.2258	0.1426
4	Brazito	4.8	5.2	2.9	0.2218	0.2162	0.1569
5	Cloversprings	4.8	2.8	1.8	0.0593	0.0572	0.0434
6	Comoro	4.9	3.9	2.4	0.1173	0.1136	0.0797
7	Contine	3.9	5.3	4.2	0.2431	0.2258	0.1399
8	Davidson	2.3	4.0	5.9	0.1483	0.1200	0.0541
9	Gila	4.9	5.8	2.9	0.2825	0.2778	0.2083
10	Grabe	4.8	5.0	2.4	0.2016	0.1977	0.1555
11	Hayhook	4.5	5.5	4.7	0.2611	0.2458	0.1346
12	Holtville	4.7	5.4	2.6	0.2405	0.2357	0.1831
13	Laveen	4.2	5.2	3.8	0.2291	0.2162	0.1389
14	Mohave	3.7	5.2	4.4	0.2353	0.2162	0.1301
15	Molokai	1.8	3.0	4.9	0.0844	0.0655	0.0330
16	Nicholson	5.4	6.8	4.8	0.4078	0.4023	0.2304
17	Pima	4.9	5.2	3.1	0.2220	0.2162	0.1503
18	Pinaleno	4.1	5.1	4.3	0.2226	0.2068	0.1210
19	Sonoita	4.9	6.2	3.3	0.3301	0.3243	0.2337
20	Superstition	4.8	6.6	3.9	0.3842	0.3752	0.2536
21	Vint	4.4	5.3	4.2	0.2393	0.2258	0.1338
22	Whitehouse(A)	3.4	4.8	5.6	0.2056	0.1802	0.1176
23	Whitehouse(B)	2.6	4.1	5.5	0.1522	0.1267	0.0598

[1] Trade names and company names are included for the benefit of the reader and do not constitute an endorsement by the University of Arizona.

CALCULATIONS

Average Munsell color data were then converted into C.I.E. coordinates, X,Y,Z, using conversion tables published by Wyszecki and Stiles (1982) and by linear interpolation between the data provided by the tables (table 1).

The relationship between the spectral reflectance curves and color was then derived by multiple regression technique. The linear correlation between soil reflectance with smooth surface condition and the X,Y,Z color coordinates were computed for each of 23 the soil samples over each 10-nm band (fig.1).

Spectral reflectances were modeled using the correlation coefficients computed between reflectance and the C.I.E. color coordinates :

$$Rm_{ij} = a_j . X_i + b_j . Y_i + c_j . Z_i + d_j \qquad (1)$$

where Rm_{ij} is the modeled reflectance for soil i at the wavelength j ; a, b, c and d are the computed coefficients (see fig.2), and X,Y,Z the C.I.E. color coordinates derived from estimated Munsell color for soil i.

By repeating this computation for each 10-nm band, a complete spectral curve was reconstructed for each of the soil samples with smooth surface condition.

The effect of roughness on soil reflectance was determined by calculating the percent decrease in reflectance (DR_i) between 'rough' and 'smooth' conditions:

$$DR_{ij} = \frac{Rs_{ij} - Rr_{ij}}{Rs_{ij}} . 100 \qquad (2)$$

where, Rs_{ij} and Rr_{ij} are reflectance values of soil i at wavelength j, for 'smooth' and 'rough' conditions respectively.
The decrease in reflectance is almost constant with wavelength (see fig.3), so only the average decrease DR_i will be dicussed here,

$$DRi = \frac{1}{n} . \sum_{j}^{n} DR_{ij} \qquad (3)$$

where n is the number of wavebands.

The percentage of the sample surface occupied by furrow-created shadows was estimated with a 1-mm grid overlaid onto black and white photos. Since the furrows did not have very steep slopes, due to the dry condition of the soil, the north facing sides of the furrows were not strictly shadowed but rather illuminated under low sun angle.

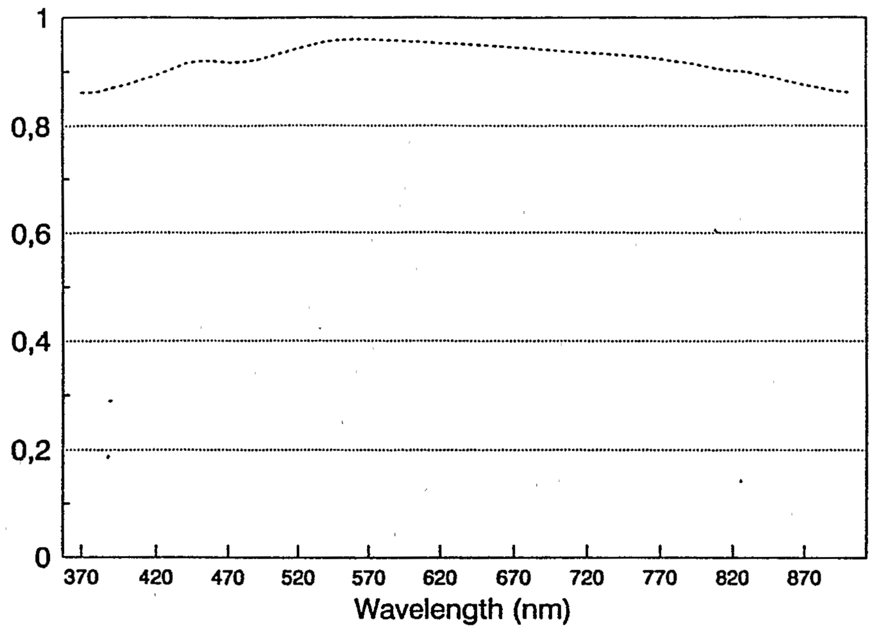

FIGURE 1. Correlation coefficients (r) between measured and modeled reflectances as a function of wavelength.

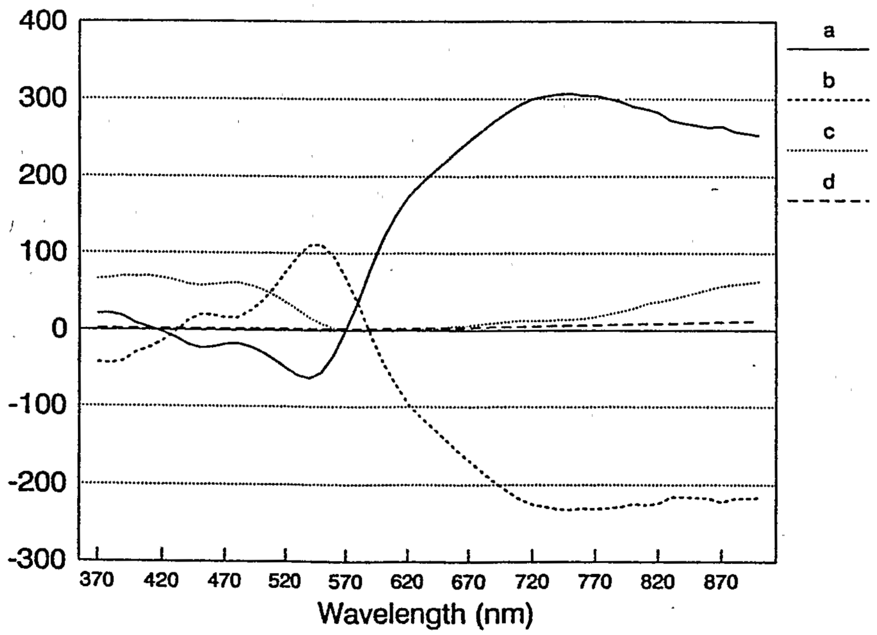

FIGURE 2. Coefficients of the multiple linear regression used in modeling soil reflectance from C.I.E. color coordinates (see equation (1) in text).

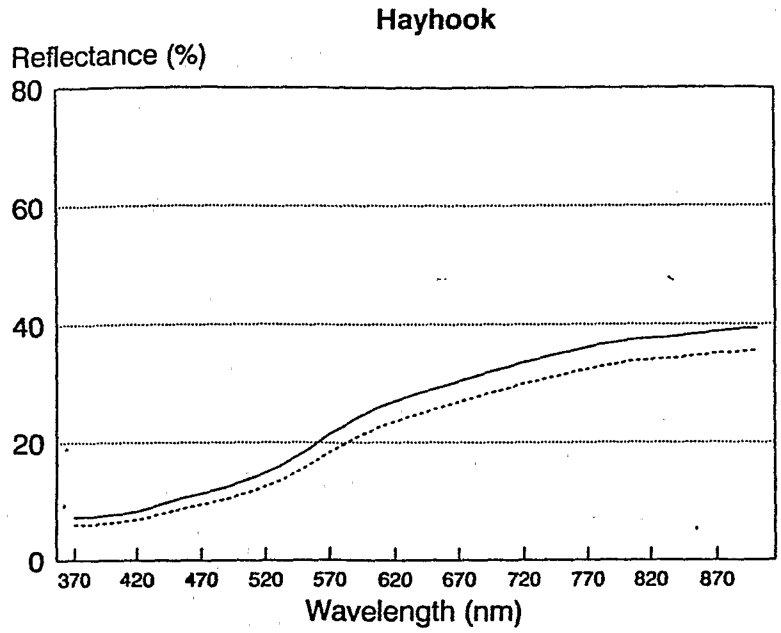

FIGURE 3. Influence of roughness on soil spectral reflectance. Example of Hayhook soil (solid and broken lines correspond to 'smooth' and 'rough' surface conditions, respectively).

RESULTS and DISCUSSION

modeled spectral reflectance curves of the 23 soils satisfactorily roduced the measured soil curves (figs.4 and 5).

exemple of an almost perfect fit between modeled and measured soil spectra is wn in the Contine soil (fig.4a). Fig.4b shows a poorer prediction of soil ctra from color data in the near infrared. Considering the results for the le set of curves (fig.6) maximum differences between modeled and measured ves were observed in the near infrared. This is not surprising since color is definition related only to the visible part of the spectrum.

is interesting to note that only three parameters were needed to correctly oduce both the monotonous and the undalating curves (compare a and b in 5). However, one soil sample showed an important discrepancy between modeled observed curves (Holtville soil, fig.7). The modeled reflectance was higher the measured one.

rently that this soil was mainly composed of granulated aggregates of 1 to size, whereas the other soils had much finer and powdery structures. That liar structure might have induced a significant decrease in the reflectance.

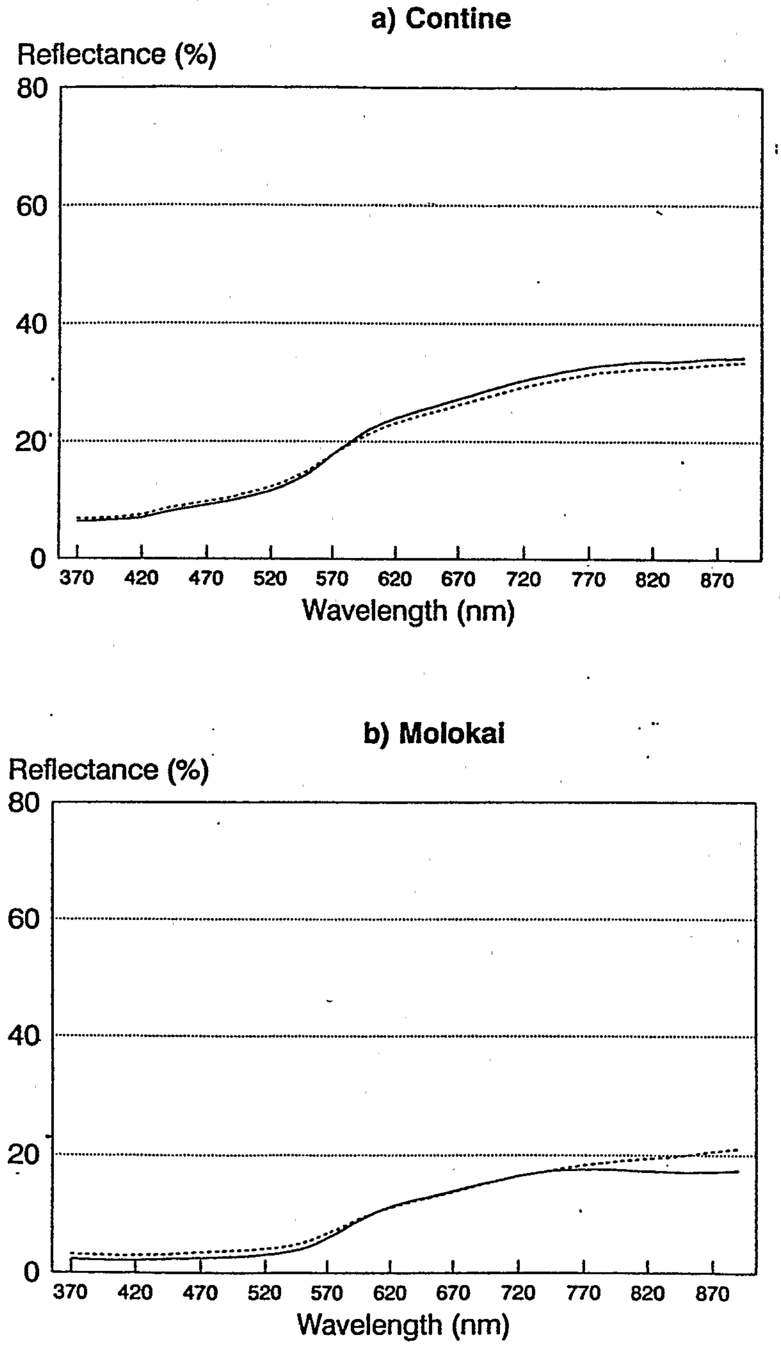

FIGURE 4. Example of measured (solid lines) and modeled (broken lines) soil spectral reflectance with similar curves shapes.

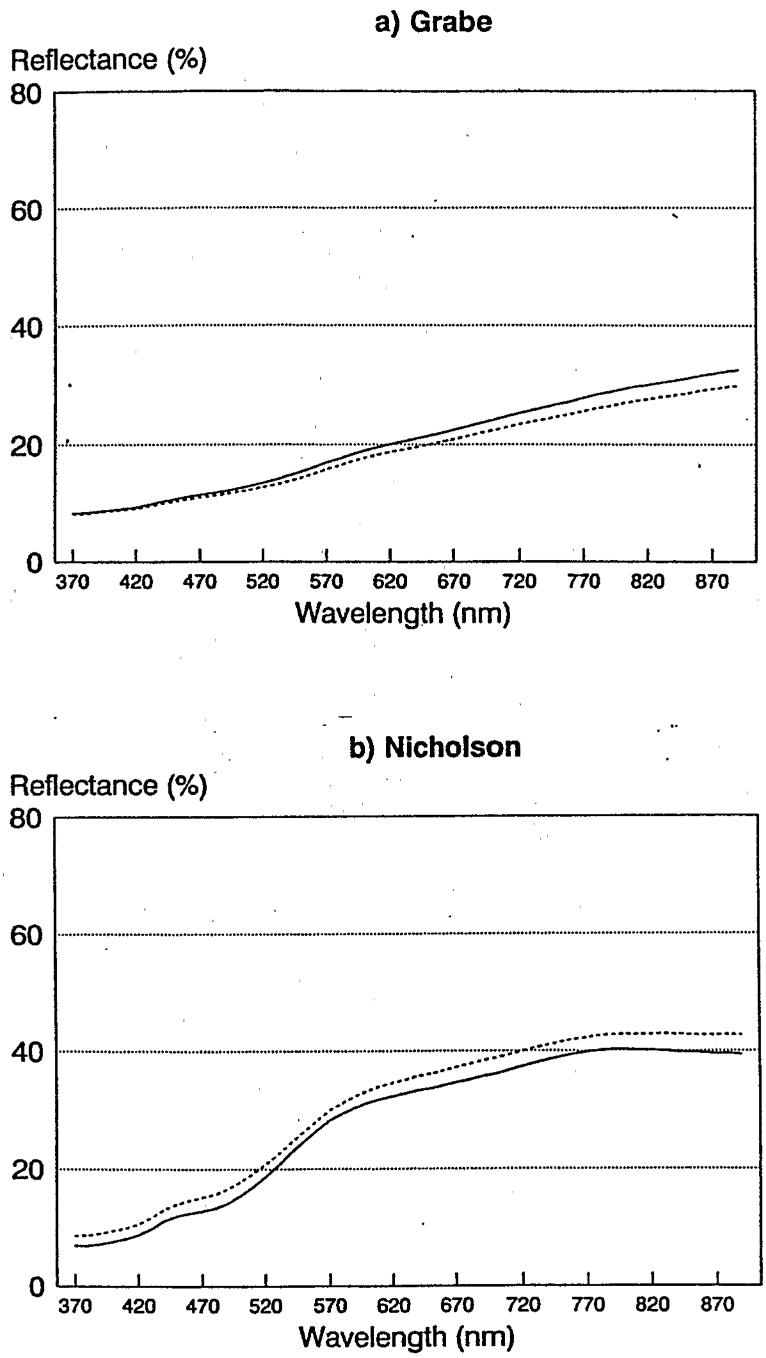

FIGURE 5. Example of measured and modeled soil spectral reflectance with different curves shapes (solid lines are measured and broken lines are modeled data).

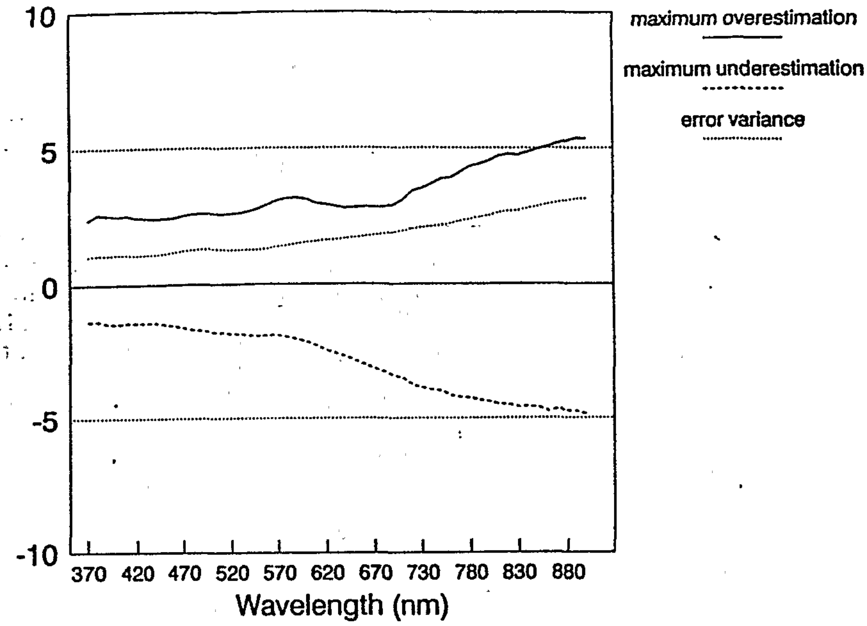

FIGURE 6. Differences observed between modeled and measured reflectances (%) as a function of wavelength (solid lines are measured and broken lines are modeled data).

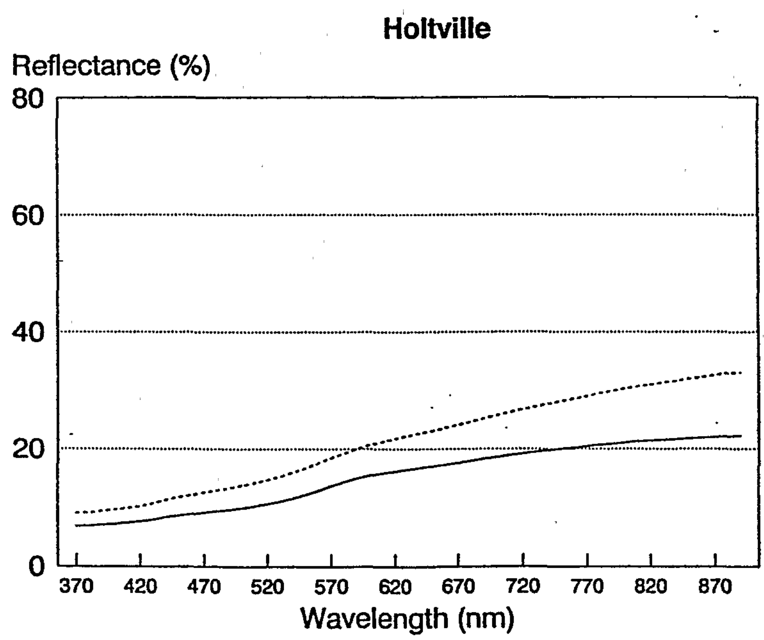

FIGURE 7. Holtville soil sample showing a discrepancy between measured and modeled reflectance curves (solid lines are measured and broken lines are modeled data).

The effect of furrow-created roughness was to significantly reduce the reflectance over all wavelengths (see example in fig.3). This was not very consistent, however, with the percentage of 'shadows' created at the surface (table 2). This is related to the fact that all samples did not have the same surface geometry when rough. The variability of soil texture and the technique used to simulate roughness did not create the same 'furrow pattern'. Thus, only a general effect of the roughness can be discussed here.

When considering a furrowed surface, its reflectance can be estimated by using the previous model to simulate the spectral reflectance of a smooth surface, and then apply an average diminishing factor of 12 % (see table 2). The average error of this second step in estimating the percent reflectance of soil samples is around ±1.5.

Table 2. Influence of roughness on the mean reflectance. Example of 13 selected soils.

Soil name	Reflectance difference(%)	Relative decrease (%)	Estimated shadow (%)
Brasito	1.2	6.1	40
Cloversprings	0.8	10.1	36
Comoro	2.2	17.4	45
Contine	1.6	7.3	44
Grabe	2.8	13.9	35
Hayhook	2.9	13.0	48
Holtville	0.8	6.3	38
Kario	3.1	7.1	39
Mohave	3.0	13.4	43
Molokai	1.4	14.1	47
Superstition	6.0	19.8	53
Whitehouse (A)	1.7	9.0	40
Whitehouse (B)	2.3	15.2	45
mean	2.3	11.7	42.5

SUMMARY and CONCLUSION

Color, visually estimated using simple, inexpensive Munsell charts, was successfully used to construct the spectral reflectance curves of 22 different soil samples in the visible-near infrared spectral range (370-900 nm). Both rough and smooth conditions were tested.

Further investigation is needed to clarify the influence of observer-dependent variance in color visual estimation and to develop convenient roughness assessment techniques. We also hope to be able to estimate 'roughness' by inverting satellite data with soil color data.

Whenever ground radiometric data are unvailable, the technique developed here allows one infer soil spectral properties from color data provided in already existing soil maps, reports and databases. Generating soil-background images for remote sensing data interpretation of sparsely vegetated areas is a promising forthcoming application of the results presented here.

REFERENCES

Cihlar (J.), Protz (R.), 1973. Surface characteristics of mapping units related to aerial imaging of soils. Can. J. Soil Sci., 53 : 249-257.

Escadafal (R.), Girard (M.C.), Courault (D.), 1988. Modeling the relationships between Munsell soil color and soil spectral properties. International Agrophysics, 4(3) : 249-261.

Escadafal (R.), Girard (M.C.), Courault (D.), 1989. Munsell soil color and soil reflectance in the visible spectral bands of Landsat data (MSS and TM). Remote Sens. Environ., 27:37-46.

Escadafal (R.), 1989. Caractérisation de la surface des sols arides par observations de terrain et par télédétection. Etudes et Thèses, Orstom, Paris, 317 p.

Graetz (R.d.), Gentle (M.R.), 1982. The relationships between reflectance characteristics in the Landsat wawebands and the composition and structure of an Australian semi-arid shrub rangeland. Photogramm. Eng. Rem. Sens., 48 (11) : 1721-1730.

Huete (A.R.), 1988. A soil adjusted vegetation index (SAVI), Remote Sens. Environ., 25:295-309.

Huete (A.R.), Jackson (R.D.), 1987. The suitability of spectral indices for evaluating vegetation characterisitics on arid rangelands, Remote Sens. Environ. 23:213-232.

Huete (A.R.), Post (D.F.), Jackson (R.D.), 1984. Soil spectral effects on 4-Space Vegetation. Remote Sens. Environ. 15:155-165.

Munsell Colour Company, 1971. Munsell soil colour charts. Kollomorgen Corporation, Baltimore, 17 pl.

Pendleton (R.l.), Nickerson (D.), 1951. Soils colors and special soil color charts. Soil Science, 71, 35-43.

Post (D.F.), Levine (S.J.), Bryant (R.B.), Mays (M.D.), 1989. Determination of the soil colors by the Munsell System. Agronomy Abstracts : 269.

Pouget (M.), Mulders (M.a.), 1988. Report of the ISSS working group "Remote sensing of the soil surface". Description of the landsurface for correlation with remote sensing data. 5th ISSS Symposium of the Working Group Remote Sensing, Budapest, 11-15/04/88.

Soil Survey Staff, 1975. Soil taxonomy. A basic system of soil classification for making and interpreting soil surveys. Agric. Handb. 436. , Department of Agriculture, Washington D.C.

Spiridinov (H.), Kuncheva (R.), Misheva (E.), 1971. Results and conclusions from soil and vegetation reflection coefficient measurements. Adv. Space Res., 1(10) : 111-114.

Tueller (P.T.), 1987. Remote sensing science applications in arid environments. Rem. Sens. Environ., 23 : 143-154.

Wyszecki (G.), Stiles (W.S.), 1982. Color science : concept and methods, quantitative data and formulae. Wiley, New York, 2nd edition, 950 p.