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APPLICATION OF MULTISPECTRAL REFLECTANCE STUDIES OF SOILS: PRE-LANDSAT

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I. ABSTRACT

It was recognized in the 1960's that measuring the spectral, spatial and temporal variation of electromagnetic fields reflected and emitted from the Earth's surface had many potential applications in the field of agriculture. As a result, computer-implemented pattern recognition techniques were used to analyze multispectral data for the purpose of delineating soil differences. Spectral data were obtained (1) in the laboratory by scanning soil samples with a double-beam spectrophotometer (Beckman DK-2A) and (2) in the field by scanning large areas of soils with an airborne multispectral scanner.

The results obtained through this early research clearly illustrated relationships between the reflected and emitted energy from soils and other physical and chemical properties of those soils. The possibility of sampling large geographic areas and obtaining information about various soil parameters within a relatively short time period appeared to be of great value to potential users, i.e., soil surveyors, soil conservationists and other resource management personnel.

II. INTRODUCTION

In January 1966 the Laboratory for Applications of Remote Sensing (LARS), Purdue University, was chosen by the U.S. Department of Agriculture, in cooperation with the National Aeronautics and Space Administration, to develop remote sensing, pattern recognition techniques for application to agricultural and forestry resources. Investigations were initiated in the study of spectral, temporal, and spatial reflectance and emittance characteristics of plants, water and soils and other agricultural features[5,10,11]. The principle that energy is either absorbed, reflected, transmitted or emitted from objects in specific wavelengths in amounts that are characteristic to a particular kind of matter suggested to soil scientists at LARS that many soil parameters could be measured through the use of their spectral variations[4,6,8]

W. L. Kubiena[9], world renowned European pedologist, wrote in 1938, "Pedology as a natural science, after a promising start, still is developing slowly. We are not much further with pedology in its present stage than we were in the middle of the last century." Kubiena repeated these words about pedology when he visited Purdue University in 1965, one year before LARS was established.

In contrast to Kubiena's statement, now we are able to say that within the past decade significant advances have been made in the development of airborne and satellite-borne remote sensor systems which make it possible to obtain vast quantities of earth resources data over large geographical areas within a very short time[7]. Such data acquisition capabilities, coupled with computer-implemented analysis techniques, provide a rapid capability for inventorying and monitoring earth resources[1,2,3,12]. Instrumentation in this research to measure the radiation properties of different soils in the various portions of the electromagnetic spectrum included a DK-2A spectrophotometer and an aircraft optical-mechanical scanner.

III. SPECTRAL CHARACTERISTICS OF SOILS

Laboratory studies were essential for developing an understanding of energy interactions with the soil. In one important study spectral measurements were obtained on 250 soil samples representing twenty-two soil series, ten textures, and four drainage profiles. In addition, samples of betonite, muscovite and kaolinite were investigated. This study provided information

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about which wavelength bands were useful for observing spectral variations in soil; additional knowledge was gained about the influence of some chemical and physical soil properties on reflected energy. Wavelengths in both the visible and infrared portions of the spectrum were found to be important. For example, the 0.58-0.61 μm visible band was found to be extremely useful for quantitative characterization of soil color. Soil textures were best differentiated in the 0.73-0.76 μm and 0.88-0.90 μm spectral ranges. The potential for using reflectance measurements to determine soil moisture contents was shown by analysis of the three water absorption bands, 1.43-1.45, 1.62-1.65 and 1.91-1.94 μm. Bands at 2.07-2.09 and 2.16-2.19 μm were especially useful in quantifying the clay content of the soils. In both bands the high reflectance values were related to the soil with generally less than 20% clay and less than 2% organic matter.

Descriptive information for three soil series is presented to illustrate some of the important soil differences among the soils studied (Table 1). Reflectance values for air-dry and moist samples of these three series were determined for eight wavelength intervals (Table 2). The Raub, a dark colored soil with high organic matter content, gave the lowest reflectance values for air dry soil in all wavebands. In general, an increase in water content results in a decrease in reflectance for all wavelengths for all three soils, although the decrease was most pronounced for the Miami.

Table 1. Descriptive information for three soil series.

	Miami	Fincastle	Raub
Texture	silt loam	silt loam	silt loam
Native vegetation	forest	forest	prairie
Water holding capacity	medium	high	very high
Organic matter content	low	medium	high
Natural drainage	well	somewhat poorly	somewhat poorly
Structure	coarse granular	medium granular	moderate granular
% moisture in air-dry samples	2.5	1.0	2.7
% moisture in moist samples	33.9	49.9	59.1
Surface color	yellowish-brown 10YR 4/2	brownish-gray 10YR 3/2	very dark 10YR 2/2

IV. INITIAL SOIL INVENTORIES

The use of digital analysis of multispectral data appeared to be a useful aid for mapping soils. Therefore, a study was designed how this new technology might best be employed to discriminate meaningful soil boundaries in the field.

An area (SA1) of bare soil in the central part of Indiana (Morgan County) was selected for this study. The soils are primarily Alfisols and Mollisols developed under dense forest cover in Wisconsin glacial till, outwash or eolian materials. The multispectral data over SA1 were collected on 28 April 1967 from an altitude

Table 2. Reflectance values from soil peds of three soil series, air dry and moist.

Wavelengths in μm	Miami		Fincastle		Raub	
	Dry	Moist	Dry	Moist	Dry	Moist
0.58-0.61	22.7	6.2	22.5	13.6	12.3	5.7
0.73-0.76	29.8	8.5	29.9	19.8	17.4	9.1
0.88-0.91	34.9	10.4	34.5	23.4	24.1	14.4
1.43-1.45	46.0	8.0	46.0	16.5	39.5	11.8
1.62-1.65	48.8	13.1	49.0	29.7	43.3	24.3
1.91-1.94	52.2	3.8	48.8	6.0	39.7	3.4
2.07-2.09	54.5	8.7	52.5	17.3	45.3	11.8
2.16-2.19	54.0	10.8	50.6	21.8	43.7	15.8

of 914 meters in 18 wavelength bands. Also aerial photographs of the study site were taken within a week after the acquisition of scanner data. The photographs were used to locate ground features such as soil patterns, vegetative cover and water bodies. Based on the grayscale output of the infrared channels, ten areas were selected for training samples. Eleven wavelength bands were used in the analysis: six visible (0.40-0.72 μm) and five infrared (0.72-2.60 μm). Three surface features, green vegetation, bare soil and water were easily identified and mapped by spectral analysis (Figure 1).

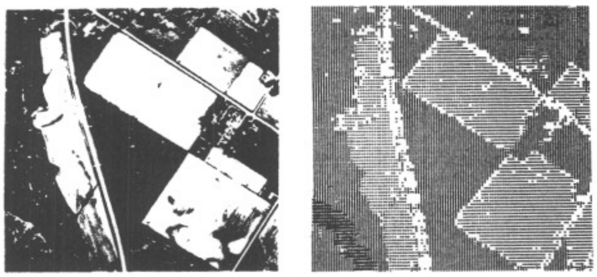


Figure 1. Aerial photograph and computer printout of green vegetation (I), soil (-) and water (M) (Kristof, 1971).

Since dark and light soil patterns can be seen on aerial photographs, a new training set was selected from the bare soil areas only. The computer was trained with new data from the dark and light colored soil areas. Vegetation and water classes were excluded. The resulting spectral map of the dark and light colored soils in the study area compared well with the variations in the dark and light colored soil areas on the aerial photographs (Figure 2a). A training set was then selected to produce six spectral separations using similar techniques as described above (Figure 2b). On closer examination of the aerial photographs a good comparison exists even in this more complex case. A thorough study of the data revealed a large standard deviation in the reflectance of some spectral classes of soils. This suggests the possibility of using spectral properties to delineate even more soil differences.

Another area (SA2), containing several large fields of bare soil, located about 5 km from the first study area, was chosen to determine whether the classification technique and accuracy could be repeated. In this area an additional large spectral variation existed among the soils. Even with this more complex spectral situation,

a. Two spectral classes

b. Six spectral classes

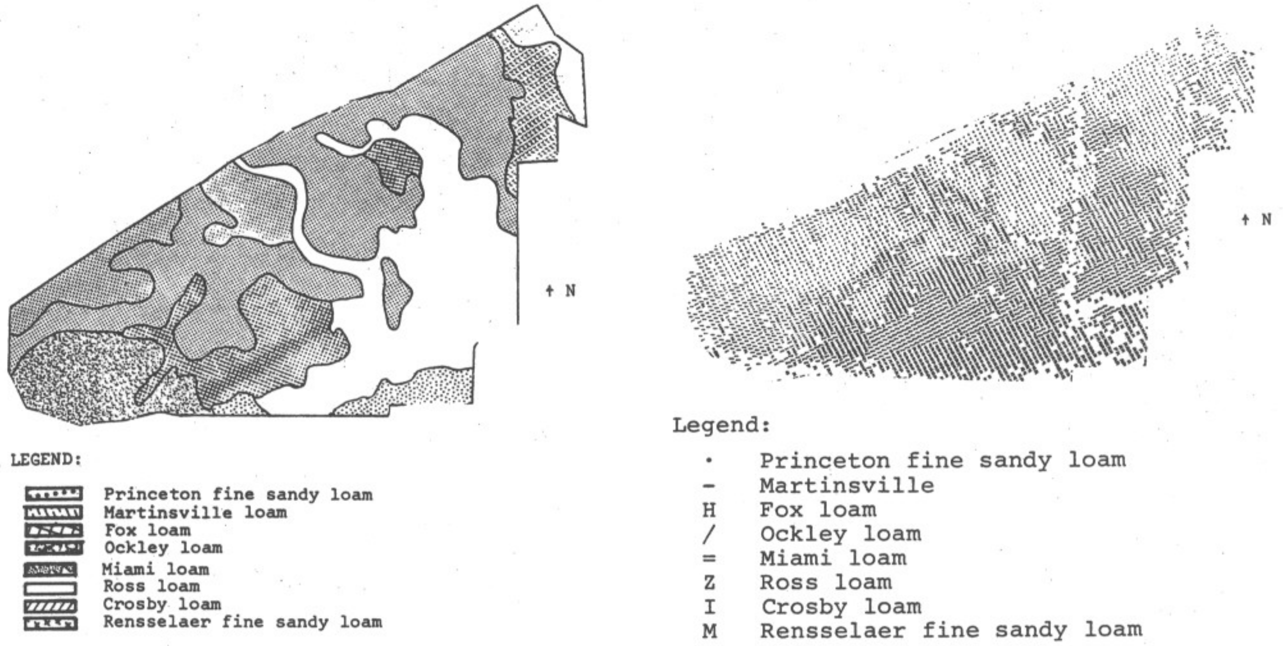
Figure 2. Spectral classes of soils of SA1 (Kristof, 1971).

the soils were easily classified into a larger number of spectral classes (eight instead of six).

The results were more striking when the computer classification output was compared with the conventionally prepared soil map where the soil had been delineated on the basis of morphology, color, structure, drainage, and texture. The eight spectral classes of SA2 corresponded reasonably well to the eight different soil series shown on the conventional soil survey map (Figure 3a and b). This study illustrated that soil surface conditions can be delineated with reasonable accuracy by spectral analysis.

A further attempt was made to map soils in a transitional zone between prairie and forest soils in Tippecanoe County, Indiana. Two soil areas, SA3 and SA4, a few kilometers from each other were chosen. Both areas contained Alfisols and Mollisols. Multispectral data were collected on 26 May 1969 from an altitude of 1300 meters. Each data point represents an area 16 x 24 meters. Eleven wavelength bands were used in the analysis: six visible (0.40-0.72 μm) and five reflective infrared (0.72-2.60 μm). Training and test samples were selected from the grayscale output in the 0.72-0.80 μm band. The sample selection was based on existing conventional soil survey maps. The area SA3 was classified into 9 and area SA4 into 7 spectral classes. Reasonably good agreement exists between the soil survey map and the spectral map of SA3 (Figure 4). The separation of two light soils, Xenia and Russell, which differ only in subsurface drainage, was not spectrally separable.

The soil map and spectral classification of the area SA4 again illustrate similar pattern delineations (Figure 5). A



a. Soil map

b. Spectral map

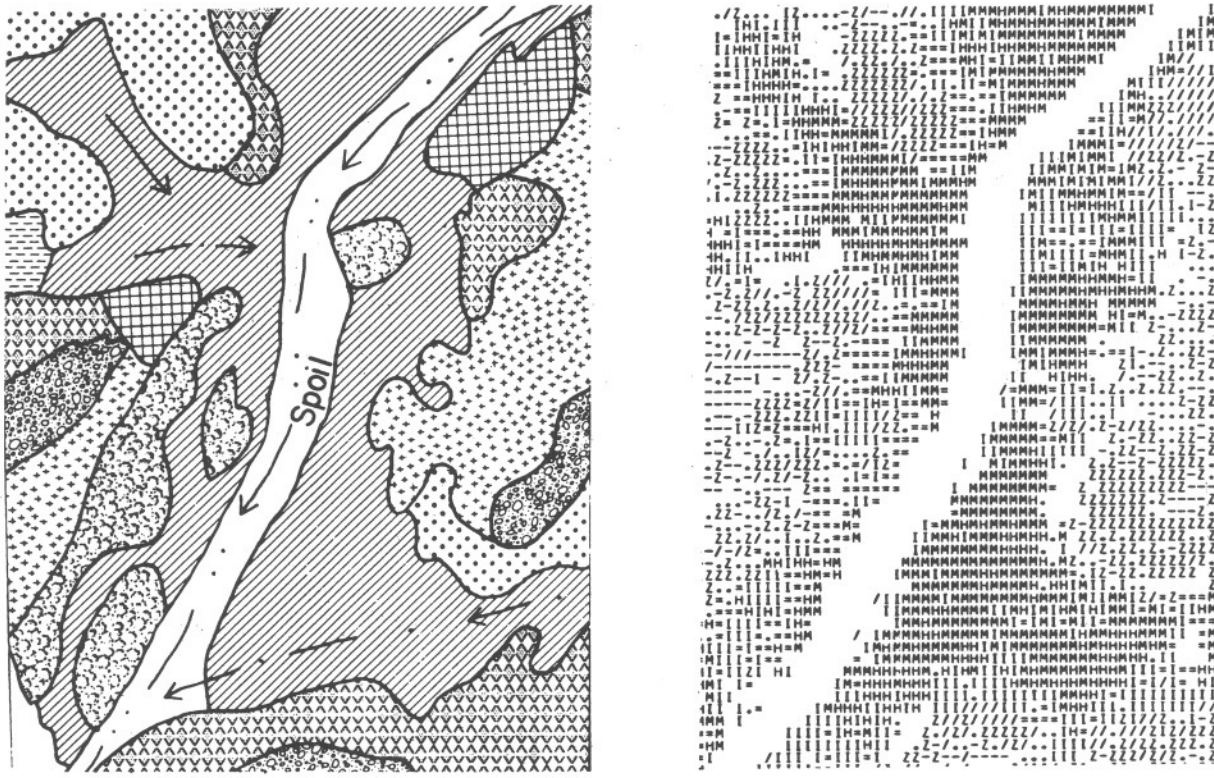
Figure 3. Maps of SA2 (S. J. Kristof and A. L. Zachary, 1974).

small portion of the Celina and Crosby soils were misclassified as Reesville. However, the Celina, Crosby and Reesville soils have similar color designations on the Munsell color chart. Color similarity was also responsible for confusion between the Brookston and Ragsdale soils.

To determine the relationship between laboratory and field spectral data, the 25 hectare farm comprising SA3 was used for more intensive soil studies. A field-sampling grid was used to collect one-kilogram surface soil samples at 32 meter intervals at a maximum depth of 2 centimeters. Mechanical and chemical analyses were performed on the resulting 197 air-dry soil samples. The samples were then separated into categories based on their mechanical and chemical characteristics. Spectral measurements were obtained by an aircraft scanner at an altitude of 1300 meters on 26 May 1969 when the surface soils were air-dry. In addition, a standard soil map of the study site was prepared. To study the relationship between soil spectral characteristics and other properties, such as surface color, and contents of organic matter, clay, silt and sand, it was necessary to obtain the quantitative field spectral values in each wavelength band. Using a grayscale printout, training samples, four picture elements (pixels) or data points in size, were located in the same relative positions as the 197 surface soil samples. This step was especially critical because a mislocation of training samples would hinder classification accuracy; it was essential that the pixels selected represent the color, organic matter content and other characteristics of the soil samples. The average uncalibrated reflectance values of the training samples were grouped into the same six categories as were the analytical results of the field samples--air-dry color, moist color, organic matter, clay, silt and sand content. Reflectance curves were then plotted to show the effects of these parameters (Figure 6a-f).

The spectral measurements of soil samples sorted by color showed that dark colored soils have much lower reflectance than light soils. The spectral values of the soils decreased when moistened while hue and saturation tended to remain the same as in the air-dry condition. The results of the computer classification of soil color were field checked and found to be in close agreement with Munsell color designation (Figure 7a).

These same techniques were applied to assess the utility of spectral analysis to delineate different levels of soil organic matter. The results were striking whether the classification was produced by analysis



Legend:

- Fincastle silt loam
- Xenia silt loam
- Russell silt loam
- Toronto silt loam
- Brookston silt loam
- Brookston silty clay loam
- Kokomo silty clay loam
- Metea sandy loam
- Del Rey silt loam

a. Soil map

Legend:

Z	Fincastle silt loam
·	Xenia silt loam
-	Russell silt loam
I	Toronto silt loam
H	Brookston silt loam
H	Brookston silty clay loam
M	Kokomo silty clay loam
/	Metea sandy loam
=	Del Rey silt loam

(Blank areas indicate "threshold" points, no classification decision made.)

b. Spectral map

Figure 4. Maps of SA3 (Kristof and Zachary, 1974).

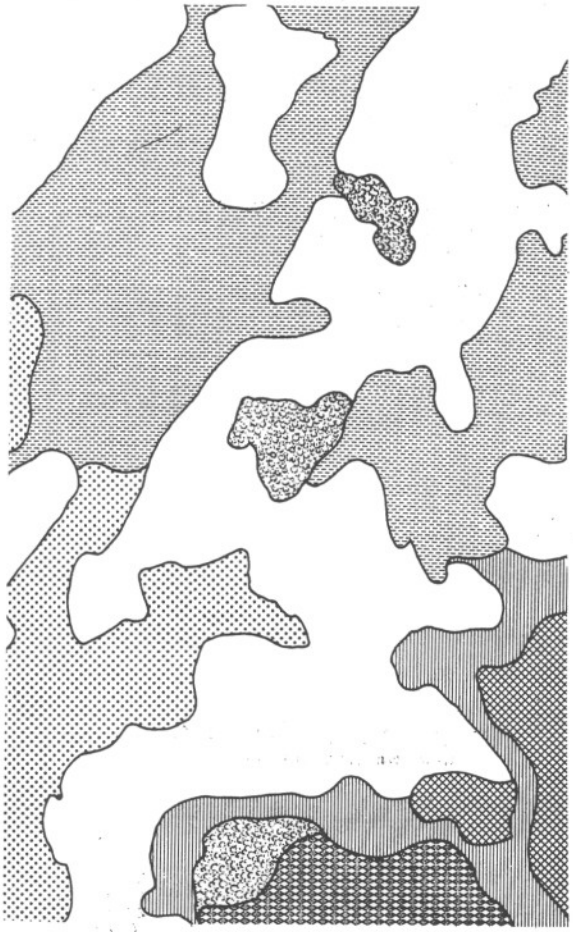
of reflectance (Figure 7b) or thermal (Figure 7c) data. It was found that the soils with more than 1.5% organic matter dramatically decreased soil reflectance throughout the reflective portion of the spectrum. Additional research has confirmed that multispectral measurements can be used to map different levels of soil organic matter.

Variations in soil reflectance can be affected by the relative proportion of clay, silt and sand in the soil. Spectral data showed a distinct decrease in reflectance with increasing clay content. On the other hand, reflectance curves for silt and sand contents showed a significant increase of reflected energy when the amount of silt and sand increased.

One of the methods commonly used to assess classification performance is to determine the percentage of all pixels in a training set which are correctly classified. The following classification performance was obtained for the spectral analysis of training sets of SA3 to identify the six soil parameters:

color, air-dry	96.2%
color, moist	98.8%
organic matter content	100.0%
clay content	59.0%
silt content	66.5%
sand content	23.1%

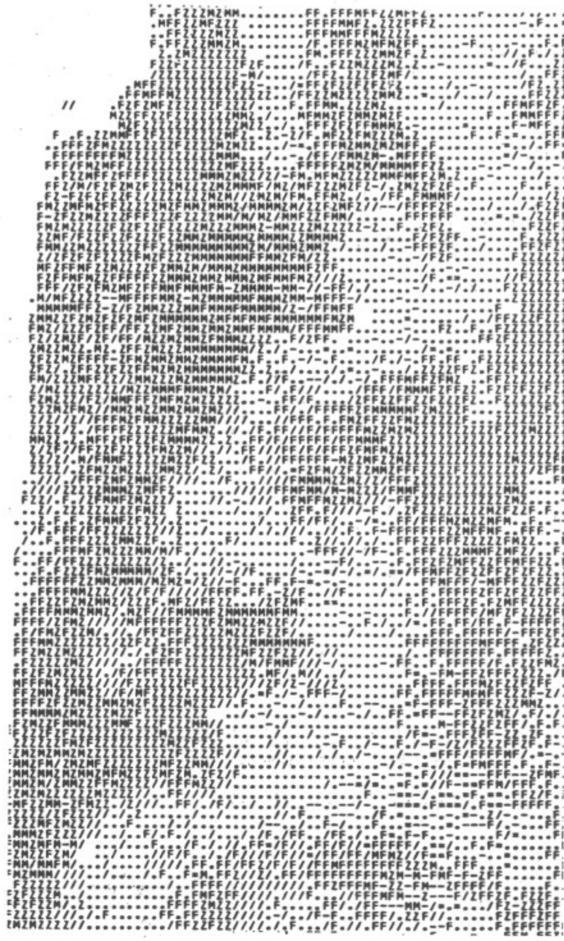
These results were verified with aircraft scanner data obtained on 6 May 1970 over an area of 6000 hectares. With the previously used 197 training samples the entire area was classified into the appropriate organic matter level categories.



LEGEND:

Ragsdale silty clay loam
Brookston silty clay loam
Brookston silt loam
Toronto silt loam
Crosby silt loam
Celina silt loam
Reesville silt loam

a. Soil map

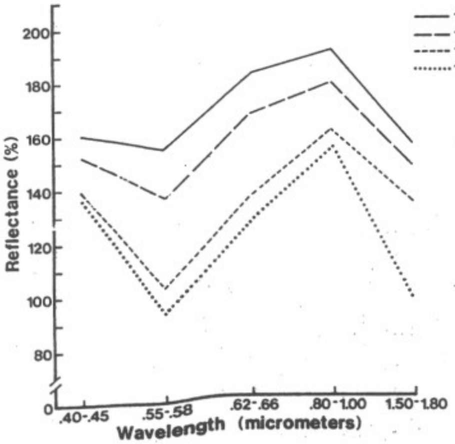


Legend:

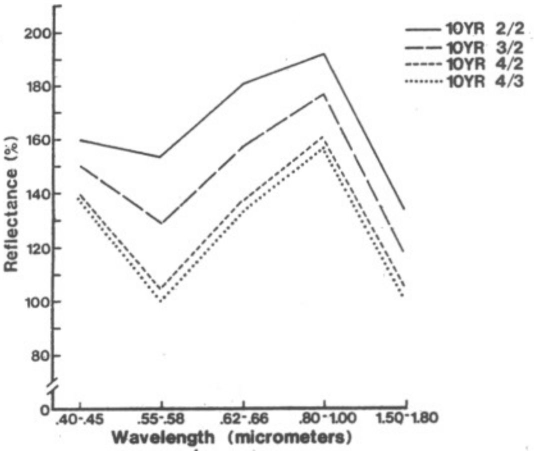
M Ragsdale silty clay loam
Z Brookston silty clay loam
F Brookston silty loam
/ Toronto silt loam
- Crosby silt loam
= Celina silt loam
· Reesville silt loam

b. Spectral map

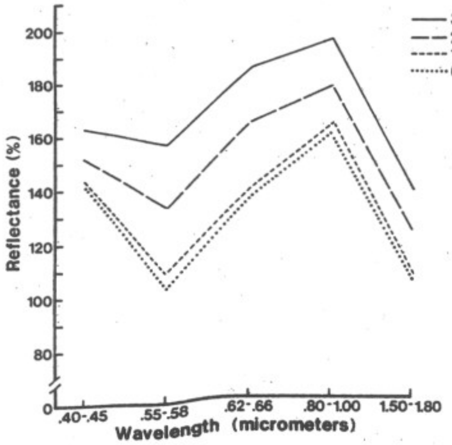
Figure 5. Maps of SA4 (Kristof and Zachary, 1974).



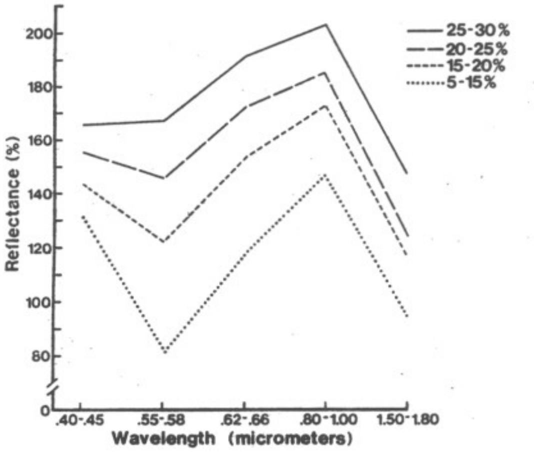
a. color, air dry



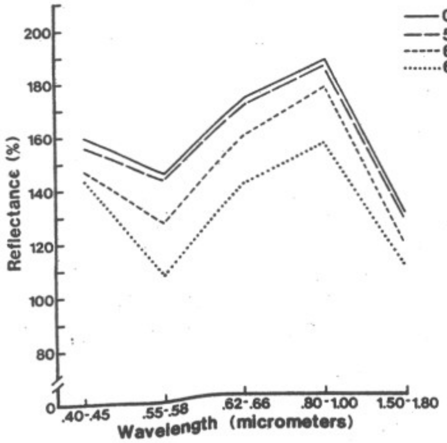
b. color, moist



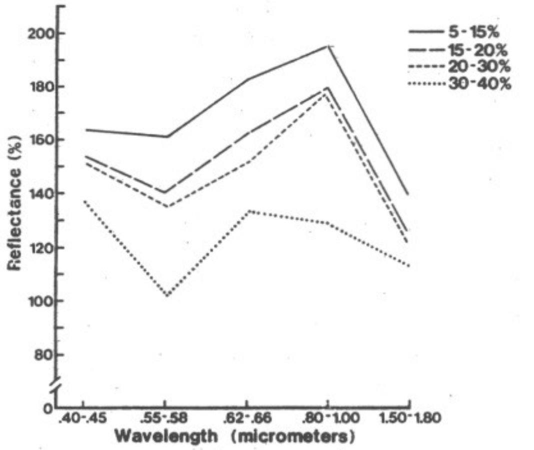
c. organic matter content



d. clay content

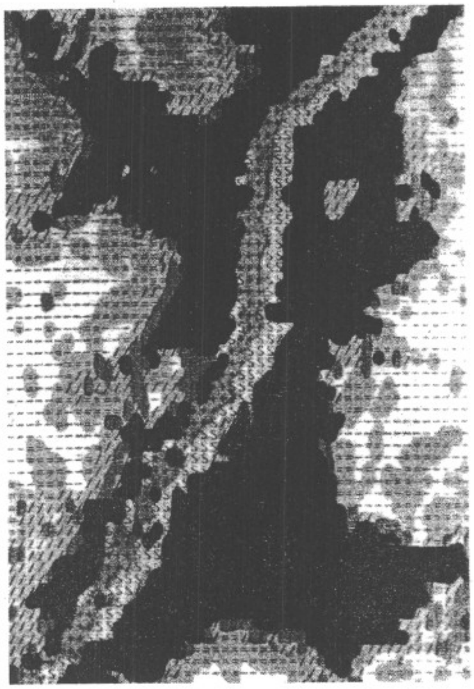


e. silt content



f. sand content

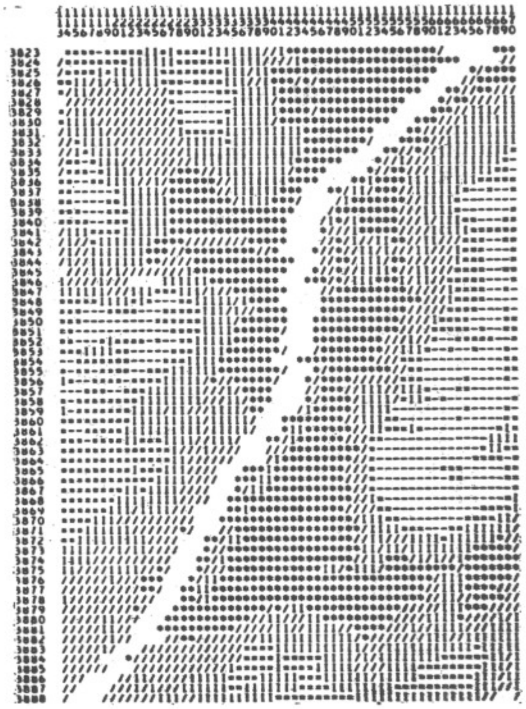
Figure 6. Relationship between soil reflectance and other soil properties (uncalibrated multispectral data).



Legend:

Munsell color notation	Symbol
10YR 6/3	-
10YR 6/2	=
10YR 5/2	/
10YR 4/2	M
(water, vegetation)	S,+

a. Soil color



Legend:

% organic matter	Symbol
0.5 - 1.5	-,=
1.5 - 2.5	/
2.5 - 3.5	I
3.5 - 6.0	*
(water, vegetation)	+

b. Organic matter content (reflectance data)

Figure 7. Spectral classes based on four different parameters determined for training sets.

Organic matter content was determined on 400 soil samples from random test fields. The overall classifiction performance was 95.6 percent for the test samples.

V. CONCLUSIONS

It should be emphasized that the technology at the time of this work was still evolving and was very experimental in nature. However, it was determined that remotely sensed radiation could serve as a useful tool for surveying, identifying, differentiating and inventorying soil and some of its important properties.

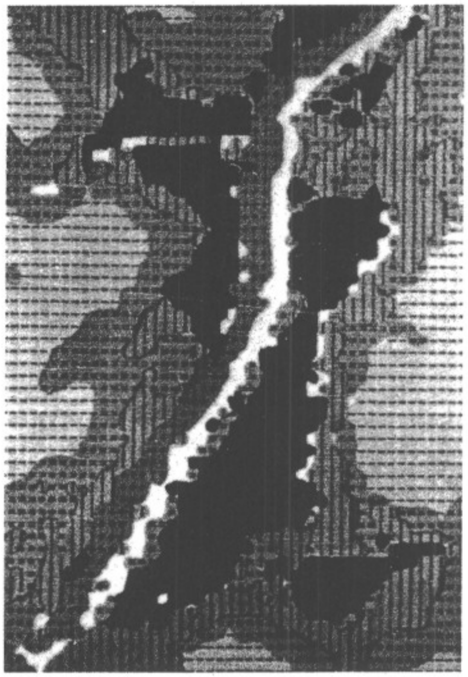
Spectral measurements collected with a spectrometer on 25 different soils increased our knowledge about the influence of the physical and chemical soil properties on soil reflectance. Also, these spectra illustrated that increasing soil moisture decreases reflectance in all wavelength bands, the effect being greater for light colored soils than for dark soils.

Analysis of multispectral data obtained by an airborne scanner over many fields of bare soil confirmed these relationships between soil reflectance and other soil properties. These results

Legend:

% organic matter	Symbol
0.5 - 1.5	*,N
1.5 - 2.5	I,F
2.5 - 3.5	Z,H
3.5 - 6.0	-,=,/

c. Organic matter content (thermal data)



Legend:

% clay	Symbol
5-15	-
15-20	=
20-25	I
25-30	M
(water, vegetation)	+, blank

d. Clay content

Figure 7. (Continued)

indicate that much of the variation in soil reflectance is a function of soil color, organic matter content, moisture content and texture.

The positive results from both laboratory and field examination of the relationships between soil reflectance and other soil properties introduced a valuable new aid for soil survey. Spectrally derived maps may delineate with reasonable accuracy important information about surface soil conditions. Inasmuch as conventional soil categories are based on both surface and subsurface soil characteristics, the techniques described in this paper can be expected to serve only as an aid to soil survey.

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Stevan J. Kristof earned a doctoral degree in Agricultural Sciences at Belgrade University, Yugoslavia and an M.S. degree in Plant Physiology at Purdue University. He joined the staff of the Laboratory for Applications of Remote Sensing (LARS) in 1967 and has been instrumental in soil studies there. He first demonstrated that soils could be mapped with an automatic technique, later applying the same technique to water, soil color, soil organic matter, moisture, clay, silt, sand and free iron contents, using data obtained by Apollo IX and Landsat. Presently he is assisting in the development of a detailed soil survey of Ford County, IL and a land resources inventory of the Big Desert area of Idaho using MSS data.

Richard A. Weismiller, B.S., M.S., Purdue University; Ph.D., Michigan State University, joined the Laboratory for Applications of Remote Sensing in 1973. His primary research interests are the relation of the spectral reflectance of soils to their physical and chemical properties and the application of remote sensing technology to soils mapping, land use inventories and change detection as related to land use. He is a member of Phi Eta Sigma, Alpha Zeta, and Sigma Xi honoraries, the Soil Science Society of America, the American Society of Agronomy, the Clay Minerals Society, and the Soil Conservation Society of America.

Marion F. Baumgardner, B.S., Texas Technological College; M.S., Ph.D., Purdue University, joined Purdue Agronomy Department staff in 1961. After two years (1964-66) in Argentina with the Ford Foundation, Dr. Baumgardner joined the Laboratory for Applications of Remote Sensing. He often serves as consultant to several international development agencies with assignments in Africa, Asia, Latin America, and Europe. He is a Danforth Associate and a Fellow of the American Society of Agronomy and the Soil Science Society of America. He is vice chairman of the International Soil Science Society's Working Group on Remote Sensing and Soil Survey and is chairman of the U.S. Agricultural Research Institute's Study Panel on Remote Sensing.