MULTISPECTRAL REMOTE SENSING OF SOIL AREAS: A KANSAS STUDY

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Multispectral remote-sensor data, coupled with computer processing techniques, provide the capability to automatically delineate surface soil distributions on the basis of spectral properties. An airborne line scanner was used to collect synoptic terrain information in 10 synchronous spectral bands spanning the visible and near-infrared radiation range. The fact that scene data are recorded directly onto computer-compatible magnetic tape allows the use of sophisticated analog and digital processing techniques for terrain analysis and automatic extraction of scene elements. Results of recognition processing of multispectral data collected over a Kansas test site demonstrate that limited surface soil mapping is feasible by this technique. Fluvial soils of varying texture were accurately delineated on the floodplains of the Kansas River and on a small tributary of the Kansas River. Recognition of upland clay soils derived from different parent materials was less successful. This upland recognition may have been adversely affected by small training set size, heterogeneous soils, and slope-illumination variations. Recommendations for continuing research include the study of soil reflectance phenomena, further development of processing techniques, and collection of multispectral data under optimal conditions.

•DESCRIBED in this report are the results of an intensive study into the use of multispectral data for automatically discriminating soils in a highway test area in northeastern Kansas. The study was carried out by the University of Michigan's Willow Run Laboratories under the sponsorship of the Federal Highway Administration in cooperation with the State Highway Commission of Kansas.

REMOTE-SENSOR DATA

Multispectral scanner data used in this study were collected at about 3:00 p.m. on March 4, 1970. The data were recorded at 3,000 ft above the terrain (approximately 4,000 ft above mean sea level). Fifteen spectral bands in the 0.40- to 13.5-μm wavelength range were recorded by 2 double-ended line scanners. These data were recorded directly onto computer-compatible magnetic tape.

Ten of the 15 spectral bands spanning the 0.40- to 0.90-μm range were used for this study (Table 1). These 10 bands were recorded synchronously. The other 5 bands in the 1.0- through 13.5-μm range were not recorded synchronously with the 10 bands and were thus not processed for use in the analysis.

In addition, 70-mm color (Kodak 8442) and color infrared (Kodak 8443) film were exposed with 60 and 20 percent overlap respectively.

KANSAS STUDY SITE

Multispectral data were collected over an area midway between Topeka and Lawrence, Kansas (site 5, described by Stallard in a paper in this Record). In the portion of the test area investigated in this study—the first 15 of the 27-mile test strip—3 major soil parent materials are found: residual limestones and shales, glacial drift, and waterlaid (fluvial) sediments. As one would expect, the soils derived from these parent materials vary considerably in their physical properties. The soils derived from fluvial materials range in surface texture from silt to clay and in plastic indexes from 5 to 20. The upland residual- and drift-derived soils are mostly clays having plastic indexes from 20 to 50 (1).

The soils are also characterized by their reflectance (color) differences (Figs. 1, 2, 3, and 4). In order of most reflective (lightest) to least reflective (darkest), the soils rank as follows: fluvial silts, upland clays derived from glacial drift, fluvial silty loams, upland clays derived from residual rocks, and fluvial clays (2). The fluvial silty loams were very similar in reflectance to upland clay soils derived from residual rocks. As with most soils, the reflectance of each sample increased monotonically with increasing wavelength. Thus, the greatest reflectance differences between these soils, for the 0.4- to 1.0-μm spectral range, occurred in the near-infrared wavelengths.

SOIL SIGNATURES

Computer-implemented processing techniques employed in this study make use of the surface spectral differences of the soil units recorded by the scanner. The differences are determined by the direct extraction of spectral "signatures" from the data, one signature for each class of interest. The signatures are obtained by locating a known sample area of each soil on an image display of the entire test area. Each sample area is known as a "training set" and is defined either by its image coordinates (digital display) or by electronic gates (CRT display). Only spectral information from the sample areas is then made available to the computer. The computer subsequently determines the mean and the variation of the electronic signals for each training set. Within each training set the spectral reflectance is likely to vary within the limits that define that soil; therefore, the spectral signatures consist of mean values and standard deviations for each channel. The means and standard deviations of all channels constitute the statistical spectral signature for the soil represented by that training set.

Six of the soil spectral signatures used in this study are shown in Figure 5. These are based on training set areas selected with the help of the State Highway Commission of Kansas.

RECOGNITION PROCESSING

Once the statistical signatures have been established, data processing procedures are straightforward. With the spectral signatures of the soil classes in its memory, the computer simply "reads" through the entire data set (all of the multispectral data recorded from the test site) and indicates the location of data "similar" to any one of the signatures. For the computer, similarity is defined by a mathematical decision rule. A number of decision rules are possible, and some are potentially more powerful than others.

The decision rule used for this processing was the "likelihood ratio." In likelihood-ratio processing, each resolution element of the data is classified as "target" or "not target" by noting whether the likelihood ratio L is greater than or less than some threshold value T. In simple form the likelihood ratio is

$$L = \frac{P_A(T)P(T/S)}{\Sigma_n P_A(B_n)P(B_n/S)} \quad \begin{array}{l} > T = \text{target} \\ \leq T = \text{no target} \end{array}$$

where

$P_A(T)$ = a priori target probability;
$P(T/S)$ = probability of target, given a data sample;
$P_A(B_n)$ = a priori probability of backgrounds n; and
$P(B_n/S)$ = probability of background n, given a data sample.

The result of this yes-no type of decision rule is a computer "recognition map." This map is an image display wherein all areas recognized as being similar to a given signature are displayed as a particular symbol or color. Areas of the test site unlike any of the signatures are left blank. Thus, only materials of interest are displayed on the recognition map.

Table 1. Band pass, spectral color, and rank of optimal spectrometer channels.

Spectrometer Channel	50 Percent Peak-Power Band Pass (μm)	Spectral Color	Rank of Optimum Channels
1	0.412 to 0.427	Violet	3
2	0.451 to 0.465	Dark blue	6
3	0.481 to 0.501	Blue	8
4	0.501 to 0.521	Blue-green	4
5	0.521 to 0.548	Green	1 (best)
6	0.548 to 0.579	Yellow	10 (worst)
7	0.579 to 0.623	Orange	7
8	0.623 to 0.674	Red	5
9	0.674 to 0.744	Dark red	9
10	0.744 to 0.852	Near infrared	2

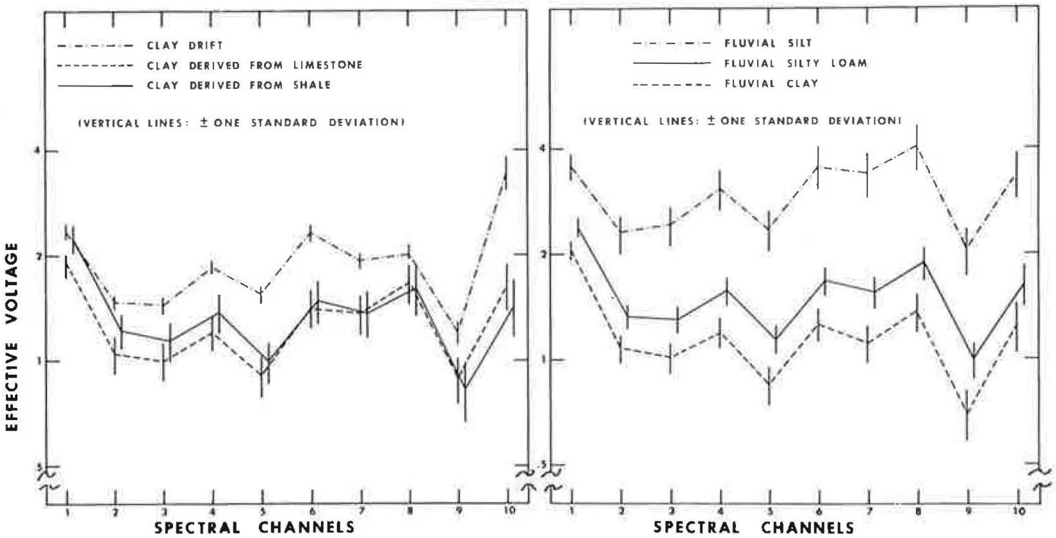
Figure 1. Fluvial silt with dark clay windows.

Figure 2. Shale-derived upland clay loam with drift soil in background.

Figure 3. Fluvial clay on a recent floodplain.

Figure 4. Silty loam soil on a recent terrace.

Figure 5. Spectral signatures of Kansas soils.



For purposes of economy, it is often advisable to reduce the number of data channels employed in processing. To determine which spectral channels are most useful, a digital program compares each signature with every other signature and determines which channels show the greatest differences between them. The ranking criterion is an input linear combination of pairwise distances. In other words, the best single channel for discriminating the soil samples is chosen first, then the channel that along with the best one is best, then the one that along with the chosen two is best, and so on. Statistically it is shown that the probabilities of misclassifying the various soils decrease with the addition of increasing numbers of data channels but that this change in misclassification probability declines very little after the best 5 or 6 channels have been selected (Fig. 6). The optimum 6 of the 10 channels were used in this study (Table 1).

COMPUTER RECOGNITION RESULTS

Ten training set areas were selected to represent the 6 major soil classes that characterize the Kansas test site: fluvial silt, fluvial silty loam, fluvial clay, clay derived from limestone, clay derived from shale, and clay derived from drift. Each of the training sets was a portion of a bare plowed field. The data were collected in early spring (1970) when as much as 50 percent of the agricultural fields were either freshly plowed (or disked) or had been plowed the previous fall. In other words, each training set signature was for the plowed soil of a cultivated field and was expected to be similar only to other plowed fields having the same kind of surface soil. No signatures were programmed for fallow fields or other nonbare soil areas. The objective was to classify soils in bare soil areas only. The recognition map results are shown in Figures 7 and 8.

Two types of error are inherent in computer-recognition maps of this sort. One type of error is a result of nonbare soil areas being classified by the computer as bare soil. The second type of error is a result of inadequate recognition of bare soil areas or areas classified as the wrong type of soil.

Analysis of the recognition results for the 15- by 1-mile data set indicates that few nonbare soil areas were incorrectly classified as bare soil. (Ground observations and color aerial photography collected at the same time as the multispectral scanner data helped establish the validity of the recognition results.) Several heavily wooded, north-facing slopes in the upland portion of the test site were spottily classified as upland clay soil. These areas were found to have accumulated as much as a foot of dead leaves from the previous fall (the trees were still bare) and had a reddish-brown appearance very similar to upland clay derived from drift.

The second type of recognition error was more serious than the first type. Of the approximately 1,100 acres of bare soil fields, 784 acres were automatically classified as one kind of soil or another. Of the classified areas, about 85 percent is considered to be correct recognition, based on landform and soil data supplied by the State Highway Commission of Kansas. Most of the incorrect classification came as a result of fluvial silty loam soil being classified as clay soil derived from shale. This misclassification is not surprising if one considers the close similarity of the signatures of these 2 soils (Figs. 1 and 2).

A marked difference between soil recognition in upland and relatively level floodplain and terrace areas occurred. In upland areas less than 50 percent of the bare fields was recognized, while almost 75 percent of the lowland soils was classified. This difference in recognition success is thought to be due to the nature of the bare fields in the upland areas. In general the fields were small and the soils were heterogeneous compared with the fluvial areas. Slope effects are thought to cause colluvial mixing of the several soils present and to effect the reflectance from these surfaces.

Soil surfaces, like most all natural objects, are not Lambertian (perfectly diffusing) reflectors. Sunlight incident on a soil surface is not reflected from that surface isotropically but is reflected rather differentially in different directions in relation to the incident angle of radiation and the nature and aspect of the reflecting surface. Also relative changes in reflectance with angle are wavelength dependent, being greater for

Figure 6. Average probabilities of misclassification of soils using from 1 to 10 data channels.

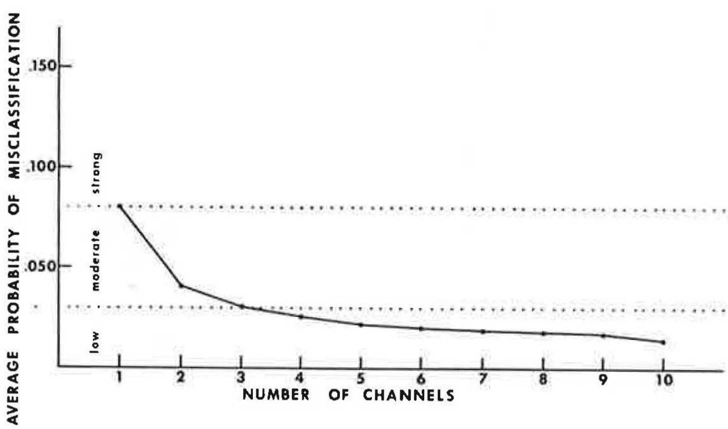


Figure 7. Multispectral soils recognition for Kansas River floodplain.

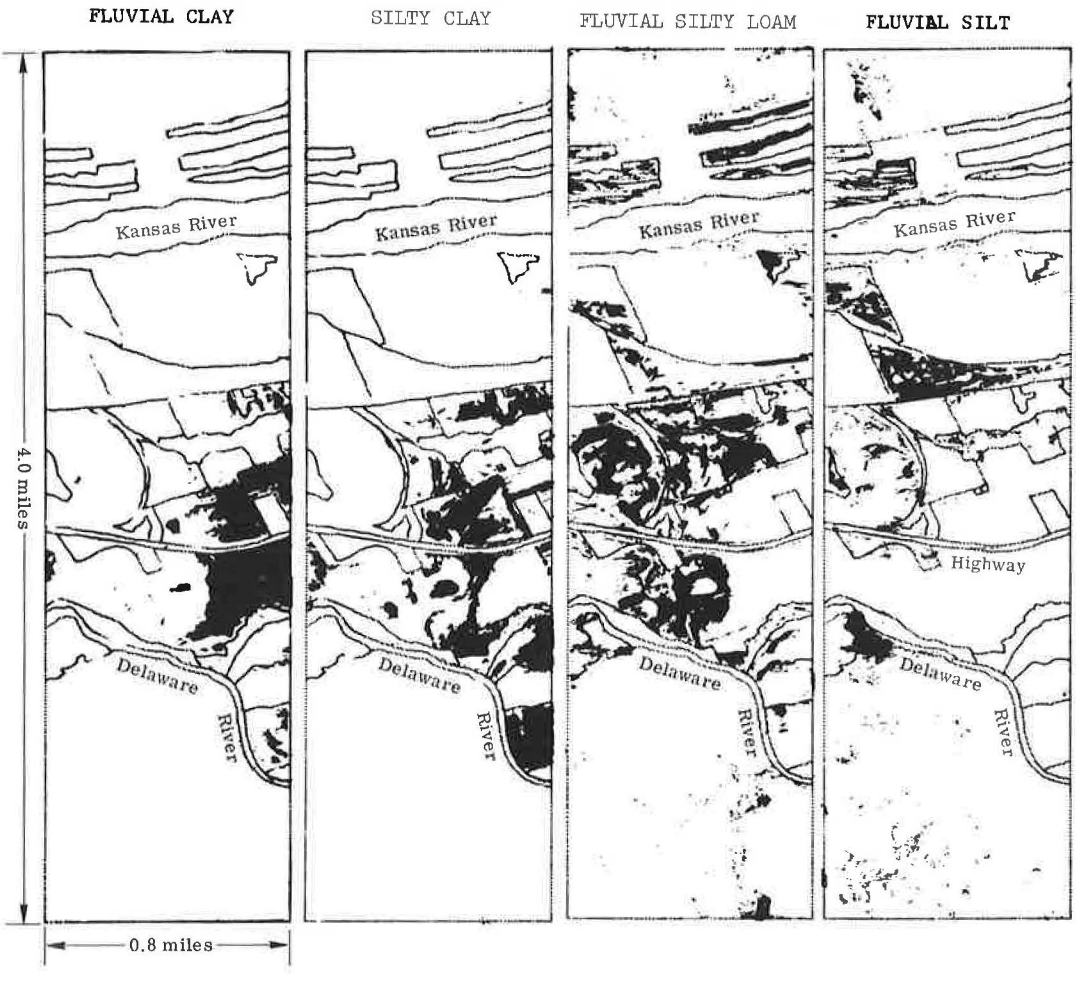


Figure 8. Multispectral soils recognition for Slough Creek floodplain area.

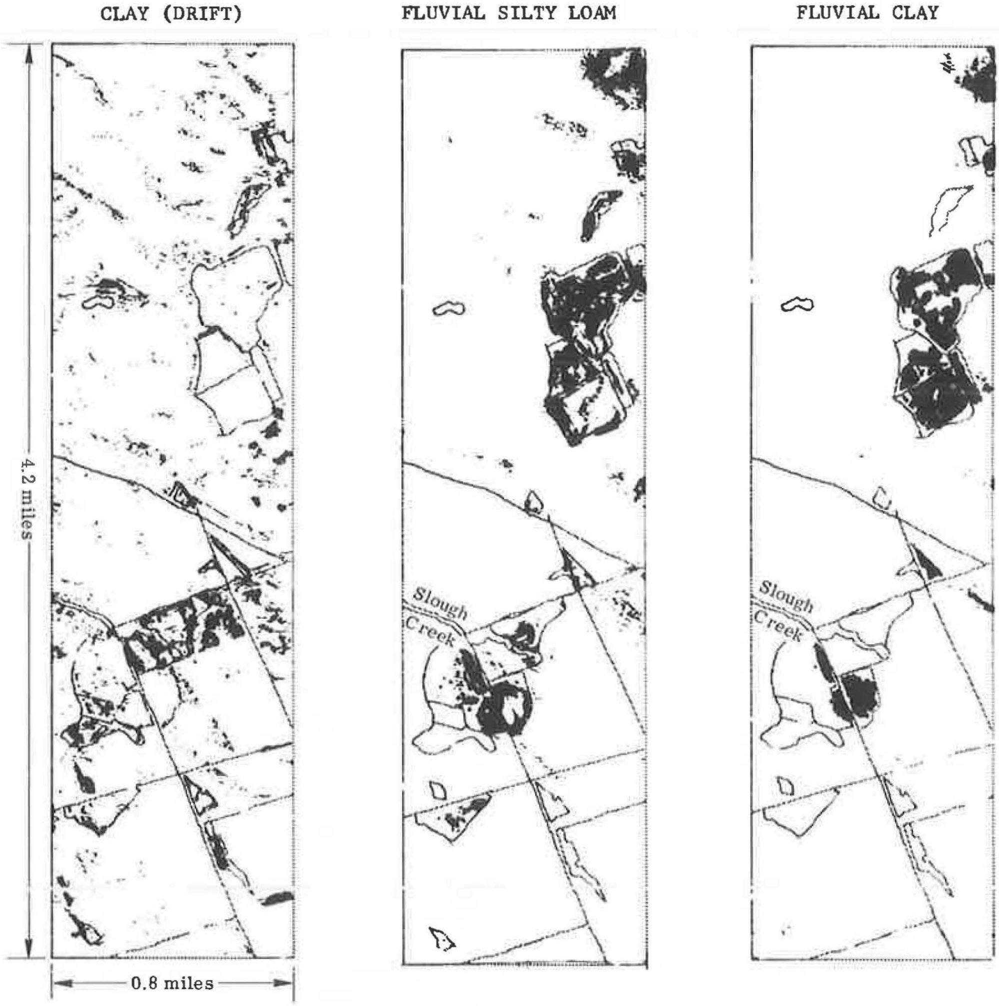
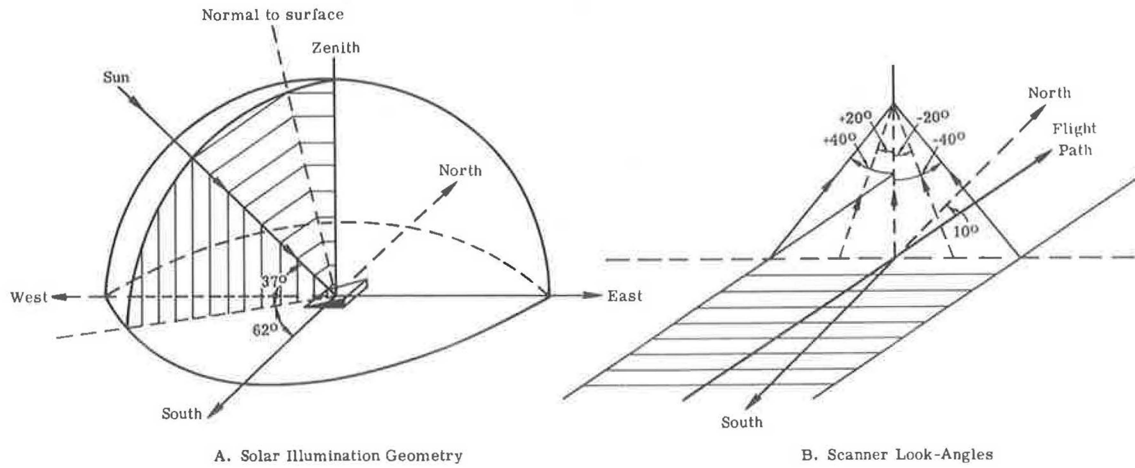


Figure 9. View-angle geometry for Kansas study site.



the shorter wavelengths than for longer wavelengths (3, 4). Figure 9 shows illumination geometry and variations in scanner view-angle geometry for this study site. Although no ground measurements were made to confirm this hypothesis, it is suggested that signatures established for several upland soils were affected by slope and scanner view-angle considerations. Signatures established for level fluvial areas were not adversely affected by slope and, thus, were applicable to the entire floodplain and terrace areas.

The recognition results for the Kansas River floodplain (Fig. 7) show the change from medium to heavy soil textures with increasing distance from the river. The change in texture closely corresponds to changes in landform, from floodplain veneer (silt deposits) to meander scars and minor terraces (silty loams) to older terrace deposits (clays). There appears to be a great deal of detail in surface variation as a result of historical meandering of a tributary, the Delaware River, across the Kansas River floodplain.

Good recognition results were achieved in the floodplain area of a small stream, Slough Creek, 12 miles north of the Kansas River (Fig. 8). Here, in addition to fluvial soils, the computer recognized small areas of clay derived from glacial drift on the floodplain. These small windows of clay were later found to be eroded areas occurring on the break in fluvial terraces. Apparently these terraces comprise reworked glacial drift, thus rendering the upland clay recognition where the subsoil is exposed to view (1).

SUMMARY

The results of this research indicate that useful and relatively accurate computer-recognition maps of soils may be developed through the use of multispectral data. There are, however, a number of important questions to be answered before this technique can become operational. Most fundamental is the question of precisely what soil parameters determine the spectral signature characteristics on which the computer-recognition results are based. In some cases, organic matter content of the surface may determine reflectance characteristics; in other cases it may be moisture, surface texture, mineral composition, or a combination of several or all of these. Second, at what level are surface spectral differences likely to delineate soil-mapping classes? Indications are that detailed soil delineations are available for bare areas in this way but that some ground observations are initially necessary to define the training sets and soil classes. What of nonbare soil areas? Signatures may be established for nonbare areas, and soils information can be inferred from the subsequent recognition maps in the same way that photo interpreters currently infer soil information from vegetation, landforms, rock outcrops, and land use—although this technique was not used in this study.

At the present state of the art, successful multispectral sensing of soils requires the following conditions: (a) the area to be surveyed should have a very large population of fields bare of vegetation at the time of the data collection flight; (b) data should be collected as near to solar noon as possible and in a direction parallel to the solar direction to minimize angle effects; (c) the terrain should be fairly level; and (d) some a priori soils information should be available for programming the computer.

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