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ENGINEERING SOILS MAPPING FROM MULTISPECTRAL REMOTE SENSING DATA USING COMPUTER ASSISTED ANALYSIS

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ABSTRACT Research objectives included 1) determine relationships if any between spectral response of soil and soil textural groups, Unified Soil Classification subgroups and selected landforms and 2) develop computer assisted techniques for engineering soils mapping of remotely sensed data.

The site in northeastern Kansas, 1.6 Km by 43 Km (1.0 mi by 27 mi), contained glacial and alluvial soils. Multispectral scanner data (0.40 to 1.80 μm) collected at 915 meters altitude (3,000 feet) were analyzed using two distinct computer techniques: the nonsupervised approach involving delineation of soil training areas directly by computer and the supervised approach entailing training area selection manually by the researcher. Computer classification of surface materials follows both methods.

Non supervised analysis results failed to show a consistant relationship between landform type and soil spectral class. Landforms correlating well displayed either unusually bright or unusually dark spectral signatures. Supervised analysis results showed a strong relationship between soil texture and soil spectral class. A moderately strong tie was shown between engineering soils groups (ML, CL, CH and OH) and their respective spectral classes, and a weak association between landform type and soil spectral class.

An analysis procedure for engineering soils mapping by computer of remotely sensed data was developed. 1. Locate cultural features by visual examination of imagery. 2. Produce generalized bare soil-vegetation-water map using nonsupervised technique. 3. Outline significant soil fields for computer training using supervised approach. 4. Computer-classify entire area based on these soil fields.

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INTRODUCTION

Soils engineers have for some time utilized various types of aerial photography in their soils mapping programs. Through examination of basic air photo pattern elements (tone, texture, size, shape, association, drainage pattern, and land use) the soils engineer has been able to obtain general information about such soil parameters as soil texture and soil moisture content. However, with the advent of such "exotic" remote sensing devices as the airborne multispectral scanner, the trained air photo interpreter should update his interpretation techniques, or risk becoming lost in the shuffle of advancing technology. In particular, he needs to become more proficient in the interpretation of image tone (or multispectral response pattern), for present-day multispectral imagery lacks the spatial resolution present in conventional aerial photography. In order to correctly interpret tones on multispectral imagery, a photo interpreter must possess a working knowledge of the electromagnetic spectrum and the manner in which different earth materials reflect light.

The electromagnetic spectrum consists of waves of energy ranging from short wavelength Cosmic rays to very long Hertzian waves (Figure 1). These waves, whose source is the sun, travel through many miles of atmosphere to strike the earth's surface. When contacting this surface, the waves of energy interact with the landscape and are either reflected, absorbed, scattered, transmitted, or re-emitted by the rocks, soil, etc. composing the landscape (Colwell et al., 1963). These five different modes of energy-matter interactions occur in different proportions for different earth materials and are also a function of the wavelength of the impinging radiation. In view of these facts, we can, in principle, identify earth materials by analyzing a

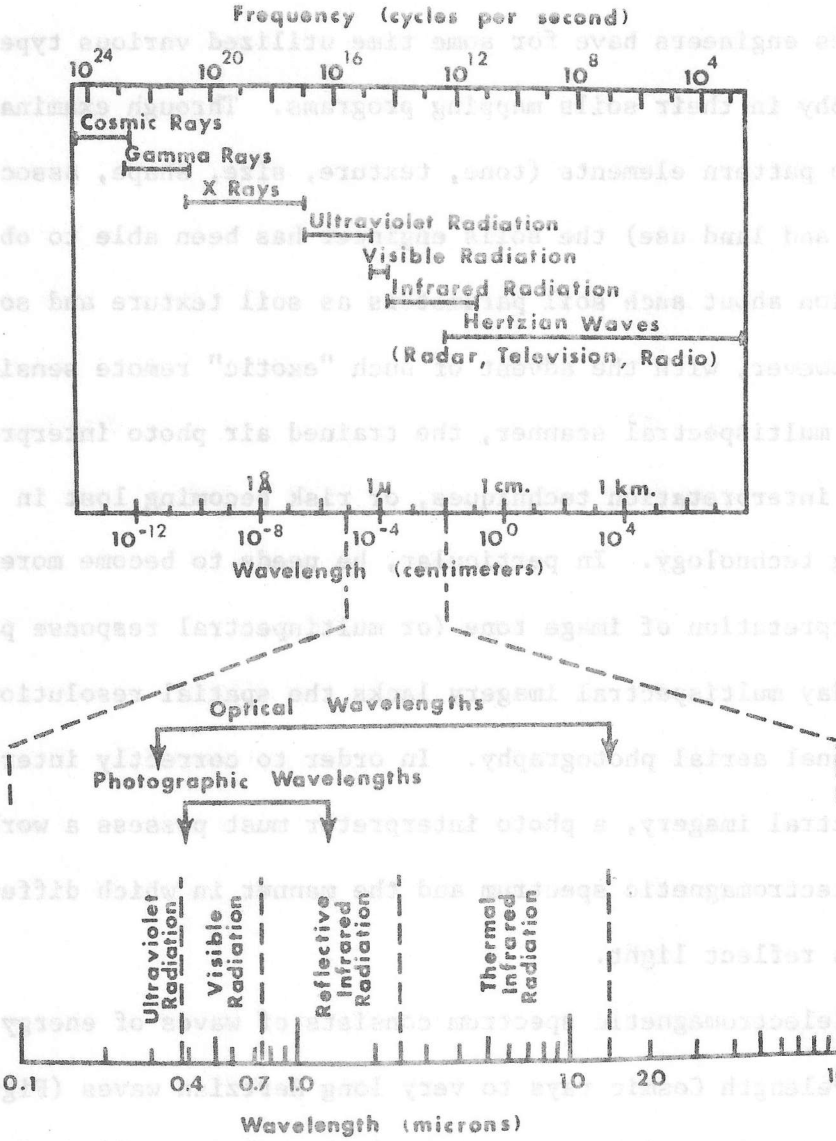

Figure 1. The Electromagnetic Spectrum (from Hoffer and Johannsen, 1969).

sufficiently detailed record of their spectral reflectance, absorption, emission, and/or scattering properties (Colwell et al., 1963). Depending upon the wavelength of light being studied, this record may consist of an aerial photo, multispectral scanner image (picture), thermal infrared image, or radar image.

Spectral studies have been conducted in the laboratory, in the field, and from aircraft in an attempt to determine the relationship between the physical and spectral properties of earth materials. Studies of different soil types* have shown soil reflectance to be a function of many soil parameters--soil color (Myers and Allen, 1968; Vincent, 1972), texture (Piech and Walker, 1972; Myers and Allen, 1968; Bowers and Hanks, 1965; Shockley et al., 1962; Al-Abbas et al., 1971), structure (Myers and Allen, 1968), surface roughness (Hoffer and Johannsen, 1969; Tanguay, 1969; Myers and Allen, 1968), moisture (Piech and Walker, 1972; Cipra et al., 1971; Tanguay, 1969; Hoffer and Johannsen, 1969; Myers and Allen, 1968; Rib, 1966; Bowers and Hanks, 1965; Shockley et al., 1963), and organic matter (Al-Abbas et al., 1971; Horvath et al., 1971; Baumgardner et al., 1970; Bowers and Hanks, 1965). As far as a soils engineer is concerned, this is unfortunate. The inability of researchers to consistently relate soil reflectance differences to differences in one specific soil property has prohibited the widespread use of remote sensing techniques in engineering soils mapping programs. However, soil reflectance has been used to provide engineering soils information in several instances. Wagner (1972) reports having used computerized aerial reconnaissance techniques to map the distribution of fluvial clays, silty clays, silty loams, and silts within the test site to be discussed in this paper. A computer-assisted study of aircraft multispectral imagery by Stockton et al.

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* Those readers interested in spectral studies of rocks, minerals, vegetation, and water should consult references (2), (7), (8), (10), (15), (17), (25), (27), and (28).

(1973) has illustrated a capability of mapping soil drainage classes. An ability to "automatically delineate" unusually wet or highly organic soils has also been shown in computerized studies of multispectral imagery (Tanguay, 1969; Mathews et al., 1973). Mathews et al. (1973) report having used a similar technique to map soil erosion classes. In addition, studies by West (1972), West (1971), Wagner (1972), Mathews et al. (1973), and Tanguay (1969) have illustrated potential for mapping landform types using terrane reflectance.

The purpose of this study was 1) to gain a better understanding of the relationship between spectral classes of soil and selected landform types, soil textural groups, and Unified Soil Classification System subgroups (in particular, the ML, CL, CH, and OH subgroups), and 2) to determine a technique for mapping engineering soils in extensive areas using computer-assisted analysis of remote sensing data.

MATERIALS AND METHODS

Description of Test Site

The test site for this study, hereafter referred to as Kansas Site 5, extends northeastward from the Kansas River across Jefferson County, Kansas (Figure 2). Most soils in Jefferson County have formed under tall prairie grasses, resulting in dark surface soils of high organic matter content and strong structure. Parent material for the soil in the test area include Upper Pennsylvanian limestones and shales, Kansan glacial till, Loveland and Peorian silts (loess), and Recent alluvium.

Upper Pennsylvanian limestones (Topeka, Deer Creek, and Lecompton) and shales (Calhoun, Tecumseh, and Kawaka) sporadically crop out along major drainage ways in the central one-third of the test site. Soils developed from

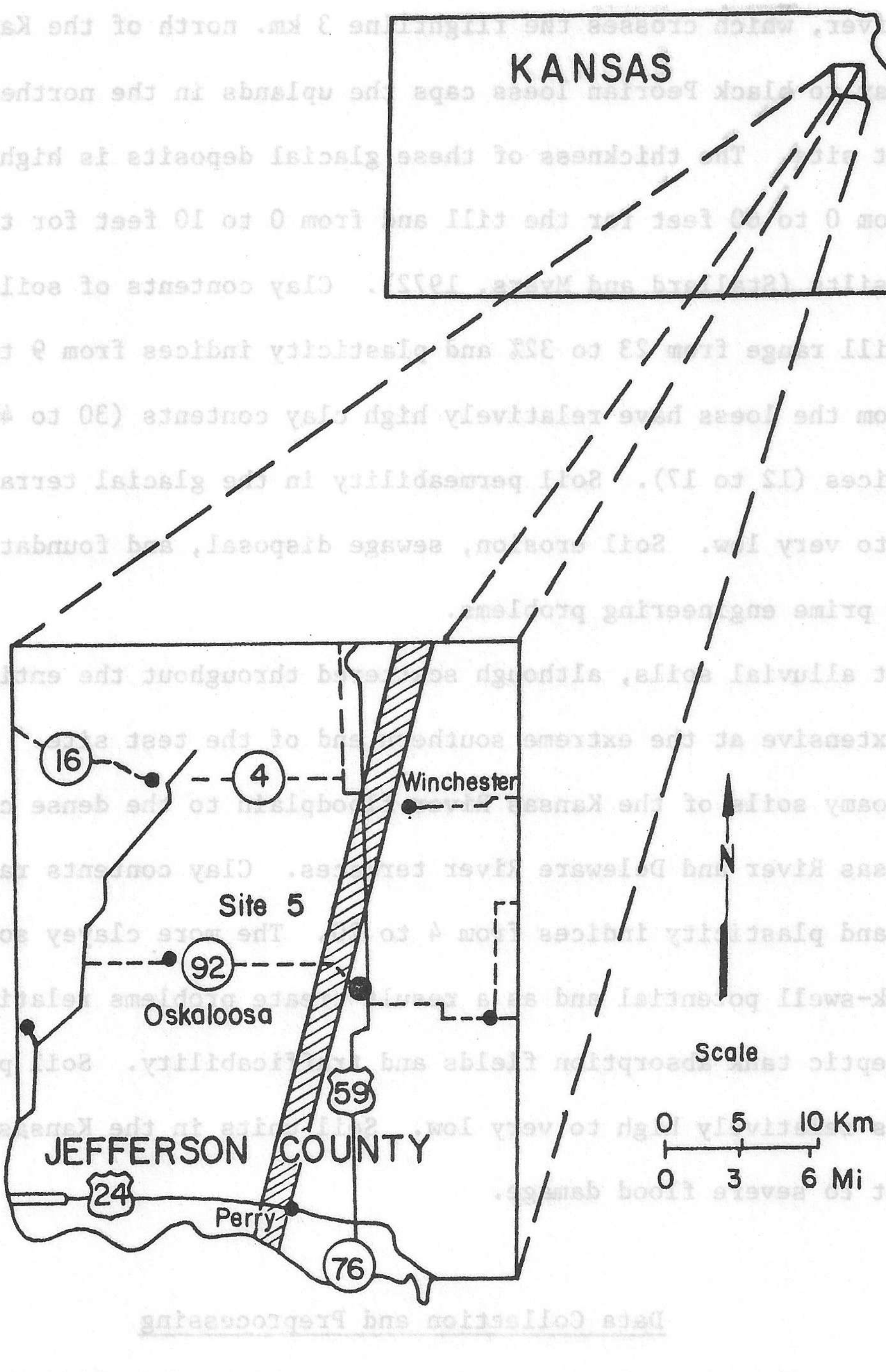


Figure 2. Location of Test Site in Jefferson County, Kansas (after Stallard and Myers, 1972).

these rock units are extremely limited in areal extent and are therefore of little consequence in this study.

Scattered areas of red to brown Kansan glacial drift occur north of the Delaware River, which crosses the flightline 3 km. north of the Kansas River, whereas gray to black Peorian loess caps the uplands in the northern one-third of the test site. The thickness of these glacial deposits is highly variable, ranging from 0 to 60 feet for the till and from 0 to 10 feet for the wind deposited silts (Stallard and Myers, 1972). Clay contents of soils derived from the till range from 23 to 32% and plasticity indices from 9 to 14. Soils derived from the loess have relatively high clay contents (30 to 42%) and plasticity indices (12 to 17). Soil permeability in the glacial terrane is moderately low to very low. Soil erosion, sewage disposal, and foundation stability constitute prime engineering problems.

Recent alluvial soils, although scattered throughout the entire flightline, are most extensive at the extreme southern end of the test site. Soils range from the loamy soils of the Kansas River floodplain to the dense clayey soils of the Kansas River and Deleware River terraces. Clay contents range from 12 to 40% and plasticity indices from 4 to 20. The more clayey soils have a high shrink-swell potential and as a result create problems relative to foundations, septic tank absorption fields and trafficability. Soil permeability in the area is relatively high to very low. Soil units in the Kansas River valley are subject to severe flood damage.

Data Collection and Preprocessing

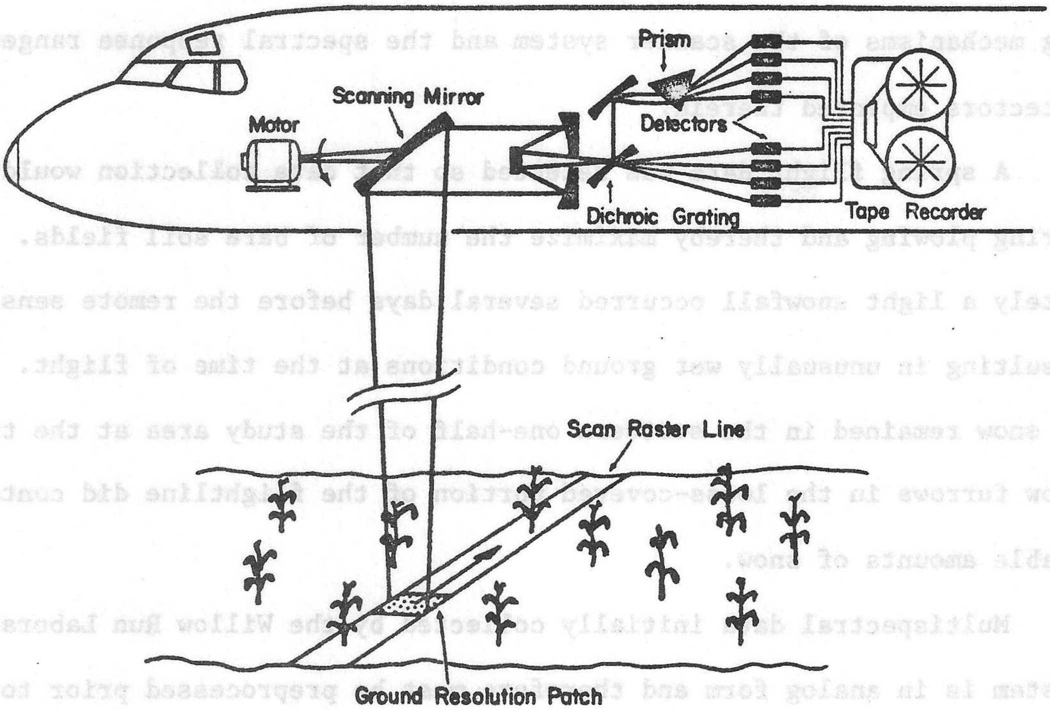
Airborne multispectral scanner data were collected at 1416 hours on April 4, 1970 from an altitude of 915 meters (3,000 feet). From this altitude, it was possible to survey a strip of terrane approximately 1.6 kilometers (1 mile) wide and 43 kilometers (27 miles) long. Spectral data in 12 discrete wavelength bands were obtained with the Willow Run Laboratory, University of Michigan airborne optical-mechanical scanner system. Figure 3 illustrates the basic working mechanisms of the scanner system and the spectral response ranges of the detectors employed therein.

A spring flight date was selected so that data collection would follow spring plowing and thereby maximize the number of bare soil fields. Unfortunately a light snowfall occurred several days before the remote sensing mission, resulting in unusually wet ground conditions at the time of flight. Although no snow remained in the southern one-half of the study area at the time of flight, plow furrows in the loess-covered portion of the flightline did contain appreciable amounts of snow.

Multispectral data initially collected by the Willow Run Laboratory scanner system is in analog form and therefore must be preprocessed prior to analysis using digital computer techniques. Scan lines produced by the aircraft system are sampled, digitized, and reformatted to produce a grid of data points for each wavelength band, or channel of interest. Each data point (image resolution element, or IRE) represents an area on the ground, whose size is dependent upon flight altitude, scanner configuration, scanner look direction and digitization rate. In this particular study, each IRE directly beneath the aircraft approximates a square, 2 3/4 meters on a side. Finally, each IRE (and associated spectral response values) is assigned a location on a computer data tape based upon scan line number and position within a scan line.

Gathering of Ground Truth Information

Location of bare soil fields was accomplished by analyzing 1/24,000 scale, 70 mm. color and color infrared aerial photography. Ground truth information on distribution of landforms was obtained from a landform map of the study



(a)

Channel	Wavelength (μm)	Channel	Wavelength (μm)
1	0.40-0.44	7	0.62-0.66
2	0.46-0.48	8	0.66-0.72
3	0.50-0.52	9	0.72-0.80
4	0.52-0.55	10	0.80-1.00
5	0.55-0.58	11	1.00-1.40
6	0.58-0.62	12	1.50-1.80

(b)

Figure 3. Airborne Multispectral Data Collection System: (a) Scanner Configuration and Scan Pattern, and (b) Spectral Response Ranges of Detectors (LARS-Purdue).

area supplied by the State Highway Commission of Kansas. Information on engineering soils was obtained from an engineering soils map and report, also supplied by the commission. Information shown on the engineering soils map and used in this study included annotations of landform type, Unified Soil Classification System subgroups, and basic soil textural groups. Landform types studied included river sand bars, old (Newman) flood terrace, young flood terrace, floodplain veneer, meander scar, floodplain, glacial till plain, and loess-covered till plain; engineering soil subgroups studied were limited to ML, CL, CH, and OH soils (see Figure 4); and soil textural groups studied were as follows: group 1- sand, sandy loam; group 2- silty, silty loam; group 3- silty clay loam, silty clay, clay loam, loam, sandy clay loam, sandy clay; group 4- clay.

ANALYSIS OF TEST SITE

Airborne multispectral scanner data collected over the test site were analyzed using automatic pattern recognition techniques developed at the Laboratory for Applications of Remote Sensing (LARS), Purdue University. These techniques utilize a library of computer programs designed to "map" the distribution of many earth materials including rock, soil, water, and vegetation. Input to the LARS programs is digital in nature and consists primarily of spectral radiance values as seen from aircraft or spacecraft. The basic LARS data analysis sequence consists of five steps: 1) Training Sample Selection, 2) Statistical Analysis, 3) Feature Selection, 4) Classification, and 5) Results Display.

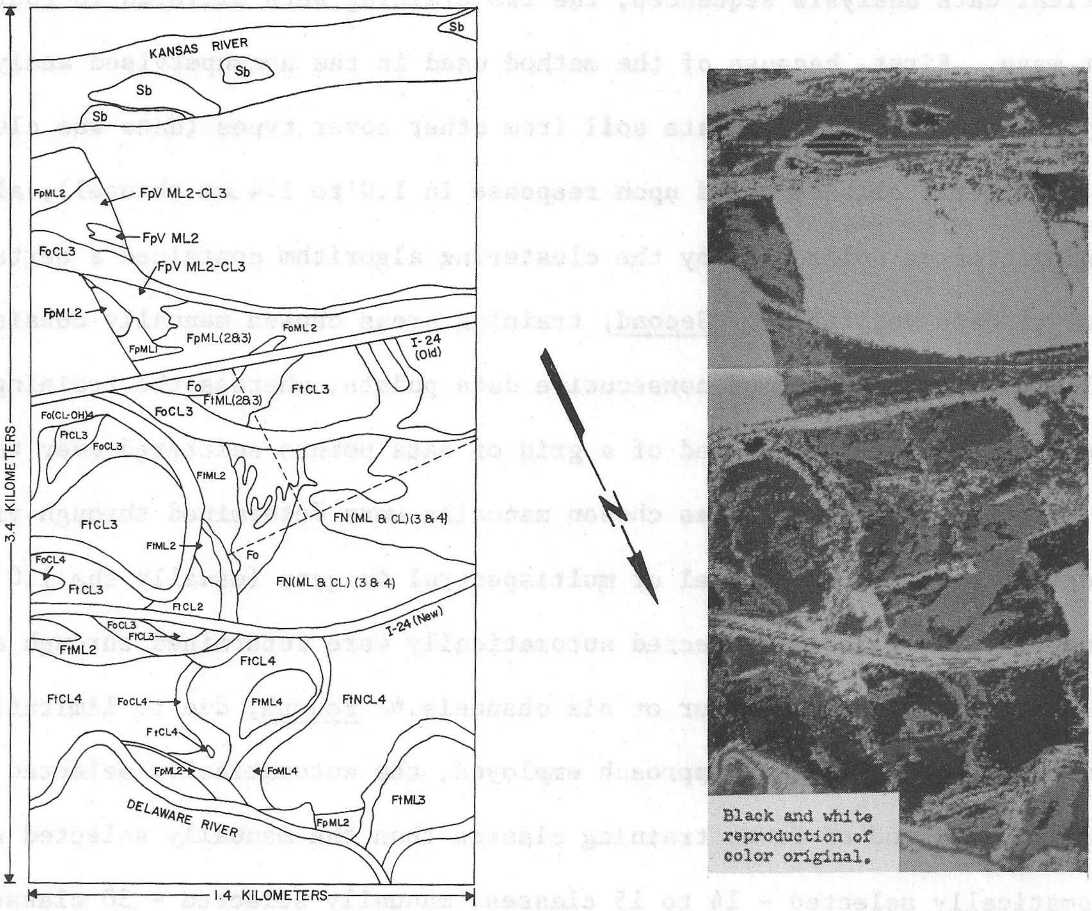
The first step in the "LARS ápproach" is the designation of areas of known classes of materials (rock types, soil types, etc.). This information, known as "ground truth," is used to train the computer to recognize similar materials.

LEGEND

Landform Types	Unified Soil Classification Subgroups	Soil Textural Groups
Young Flood Terrace.....Ft	Inorganic Silts and Fine Sands...ML	Sand, Sandy Loam..1
Meander Scar (Oxbow).....Fo	Lean Inorganic Clays............CL	Silt, Silty Loam..2
Floodplain..Fp	Inorganic Fat Clays............CH	Silty Clay Loam, Silty Clay, Clay Loam, Loam, Sandy Clay Loam, Sandy Clay........3
Floodplain Veneer......FpV	Organic Clays, Medium-to-High Plasticity, Organic Silts....OH	Clay..............4
Old (Newman) Flood Terrace.....FtN, Fn		

Example: FtCL3 designates a young flood terrace soil of low plasticity, with a texture somewhere between that of a silty clay loam and a sandy clay.

Figure 4. Engineering Soils Maps of Kansas Site 5: (a) A Conventional Engineering Soils Map (after Stallard and Myers, 1972), and (b) A Computer-generated Engineering Soils Map.


KANSAS RIVER
Sb
FpML2
FpV ML2-CL3
FpV ML2
FoCL3
FpV ML2-CL3
FpML2
FpML(2&3)
FoML2
FpML1
I-24 (Old)
Fo
FtML(2&3)
FtCL3
Fo(CL-OH)4
FoCL3
FtCL3
FoCL3
FtML2
FtCL3
FN(ML & CL)(3 & 4)
FtML2
Fo
FoCL4
FtCL3
FN(ML & CL) (3 & 4)
FtCL2
FoCL3
FtCL3
I-24 (New)
FtML2
FtCL4
FtCL4
FoCL4
FtML4
FtNCL4
FtCL4
FpML2
FpML4
DELAWARE RIVER
FpML2
FtML3
3.4 KILOMETERS
1.4 KILOMETERS
N
Black and white reproduction of color original.

(a) (b)

Figure 4.

These areas may be outlined manually (areas of uniform reflectance outlined on computer gray scale printouts or television monitor) or automatically (uniform areas determined by a clustering algorithm). In this study, soils in the test site were first mapped using training classes determined by the algorithm ("nonsupervised approach") and then using training classes selected manually from engineering soils map units within the test site ("supervised approach"). Although sets of training areas used in the two approaches were analyzed using identical data analysis sequences, the two training sets differed in four distinct ways. First, because of the method used in the nonsupervised analysis test site to initially separate soil from other cover types (data was clustered into 2 spectral classes based upon response in 1.0 to 1.4 µm channel), all soil training classes delineated by the clustering algorithm contained a certain amount of dead vegatation. Second, training areas chosen manually consisted of small rectangular blocks of consecutive data points, whereas the training areas selected by computer consisted of a grid of data points scattered over the entire flightline. Third, areas chosen manually were determined through visual inspection of only one channel of multispectral imagery (usually the 1.0 to 1.4 µm channel), while areas selected automatically were determined through statistical analysis of sets of four or six channels.* Fourth, due to limitations inherent in the clustering approach employed, the automatically selected training sets consisted of fewer training classes than the manually selected set (automatically selected - 14 to 15 classes, manually selected - 30 classes).

The second step in the LARS data analysis sequence involved statistical

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* Several alternate training sets were automatically chosen using different sets of channels. This was done to see if the quality of training sets varied with the number or type of channels chosen for clustering. Channel sets employed were as follows (see Figure 3 for detailed channel information): 1, 8, 10, 12; 2, 7, 11, 12; 1, 3, 5, 8, 10, 12; and 2, 4, 6, 7, 11, 12.

analysis of the training areas chosen in step one. Statistical parameters of each training class of interest were calculated from the spectral radiance in each multispectral scanner channel. The parameters calculated are based on an assumed Gaussian distribution of the data and include the mean, standard deviation, and covariance (Smedes et al., 1970). These parameters constitute the "fingerprint" of each training class to be used later in the data analysis sequence to classify the unknown data points into the known cover type categories.

The third step taken in analyzing the data involved the selection of the "best", or optimum set of wavelength bands to be used to map the test site. Ideally, one would like to utilize the spectral information contained in all wavelength bands (channels or features) sensed by a multispectral scanner system. Such an endeavor would prove very costly as total computer time increases geometrically as more channels are added to an analysis (Smedes et al., 1970). Luckily, however, the use of four or five channels has been shown to result in classification (mapping) accuracies very close to those achievable with more channels (Smedes et al., 1970). In light of this fact, determination of the optimum sets of channels to be used in the classification of the test site was reduced to a determination of the "best" set of four or six channels (a "best" set of six channels was determined for the supervised analysis and "best" sets of four and six channels were determined for the nonsupervised analyses). Determination of "best" channel sets was accomplished through the use of a feature selection algorithm.

The fourth step taken in the analysis sequence was the classification of all data points into the training classes using a Gaussian maximum liklihood scheme. As an additional test of the distinctness of each training class derived through clustering, additional "nonsupervised" classifications were performed by combining spectrally similar training (cluster) classes. Class similarity was arbitrarily determined through the use of a separability quotient supplied by the clustering algorithm. By combining spectrally similar training classes, it was hoped that classes representing similar landform types would be combined.

As the fifth and final step of the analysis sequence, several "soils maps" of the test site were produced and displayed. Supervised and nonsupervised classification maps of the study area were generated in two forms - line printer copy, with an alphanumeric character assigned to each spectral class of soil; and photocopy, with a different color assigned to each soil class.

EXPERIMENTAL RESULTS

The following discussions deal primarily with that portion of the test site mapped in greatest detail by the State Highway Commission of Kansas--the area of alluvial soil between the Kansas and Delaware Rivers. Occasional references are made to several other bare soil areas: a small area of alluvial soils near the town of Oskaloosa, a large plot of loessial soil near the town of Winchester, and five scattered plots of glacial till near the town of Perry.

It should also be noted that the terms "misclassification" and "classification error" are used rather loosely in the following discussion. These terms merely indicate situations where computer mapping results do not match those predicted by the writer. "Classification errors" and "misclassifications" are usually an indication that little or no relationship exists between the target of interest and multispectral response, or that improper training procedures have been used in the data analysis sequence.

Nonsupervised Mapping of Test Site

A preliminary landform map was used to check the accuracy of the cluster (soil) map produced in this portion of the study. No other soils ground truth information was available during the nonsupervised analysis of the study area.

Results indicate that a weak relationship exists between alluvial landform types of northeastern Kansas and their corresponding spectral cluster classes. In general, this relationship was strongest for landforms composed of very bright soil (i.e., floodplain veneer and river bars) or very dark soil (i.e., old flood terrace and loess covered till plain). No tie was found between areas of glacial till and spectral cluster class. Soils associated with river bars, old flood terrace, floodplain veneer, and loess-covered till plain were found to be spectrally the most homogeneous soils in the test site.

Classification of several landform units was significantly affected by the channels used in the clustering and classification steps of the data analysis sequence. The landform most affected, a large meander scar, was delineated most precisely in classifications involving, among others, channels 2 (0.46 to 0.48 μm), 7 (0.62 to 0.66 μm), and 11 (1.00 to 1.40 μm). Also, far fewer differences were noted between six-channel classifications than between four-channel classifications.

Pooling of spectrally similar cluster (training) classes was found to result in increased confusion between landform types. Two meander scars and one young flood terrace were the landform types most commonly affected.

Supervised Mapping of Test Site

The computer-generated engineering soils map (Figure 4) resulting from this portion of the study was produced using six channels of reflectance data (0.40 to 0.44, 0.62 to 0.66, 0.66 to 0.72, 0.80 to 1.00, 1.00 to 1.40, and 1.50 to 1.80 μm). Most every engineering soils map unit mapped by Stallard and Myers (1972) were successfully discriminated by the computer; but since soil training samples were taken from soil units differing in landform type, engineering properties, and soil texture, any one of these factors may have influenced the classification of each map unit. A discussion of the relationship found between these three factors and soil spectral classes will now be given.

1. Relationship between landform type and soil spectral classes.

Although an undesirable amount of thresholding (blank or null decisions on classification map) was encountered in the supervised classification of the test site (Figure 4b) computer delineation of landforms was better than that encountered previously in nonsupervised classifications. Most noticeable was an improvement in the mapping of floodplain soils. Some difficulty was, however, still encountered in separating young flood terrace from certain floodplain soils near the town of Oskaloosa.

2. Relationship between soil textural groups and soil spectral classes.

Classification of the four textural groups present in the test site was quite successful. The misclassifications that did occur were not confined to any one landform type.

FtML2 soils (number 2 designates silt, silt loam textures - see Figure 4 legend for description of other textural groups) located between the two interstate highways shown in Figure 4a were incorrectly classified as textural groups 3 and 4 by the computer.

Engineering soil map unit FoCL3 (unit in contact with I-24 (Old)) was incorrectly classified as a heterogeneous mixture of group 2 and 4 soils.

A large terrace (unit FtML3), while mapped as textural group 3, was classified as textural groups 3 and 4. This may not represent a classification error, as this unit possesses clay contents higher than other group 3 soils in the test site (Myers, 1973).

The greatest difficulty encountered in mapping soil texture involved soil unit FtCL4, located in the lower left hand corner of Figure 4a. Although soil samples taken from this unit by Stallard and Myers (1972) were definitely clayey in texture (group 4 soil), a significant portion of the unit was classified as containing group 2 soils (silts, silty loams). But again, this may not represent a classification error. A very thin veneer of silt occurs over a large portion of this soil unit (Myers, 1973).

One bare soil area deserves special mention here. Soils of map unit Fn (ML & CL) (3 & 4), Figure 4a, were classified as two soil textural groups; soils of the southeastern half of the unit were classified mostly as group 3 soils, and soils of the northwestern half as group 4 soils. Although acknowledging the presence of two soil textural groups in this unit, Stallard and Myers (1972) did not actually delineate them. Two soil textural groups were mapped in this area by SCS personnel (U. S. Dept. of Agriculture, Soil Conservation Service, 1972); soils mapped in the southeastern half of the unit (silt loams) were indeed coarser textured than those mapped in the northwestern half (silty clay loams).

3. Relationship between Unified Soil Classification System subgroups and soil spectral classes.

Delineation of ML, CL, CH, and OH engineering soils groups was good, but not as accurate as the delineation of soil textural groups. Most misclassifications involved inorganic silts and fine sands (ML soils).

Soils in unit FtML3 were classified as CL soils. This misclassification may be due to unusually high clay contents in this unit (see - 2. Relationship between soil textural groups and soil spectral classes).

One young flood terrace deposit labled FtML4 in Figure 4a was partially thresholded, the rest being classified as CL soil. One would not have expected the entire landform unit to be classified as one spectral class, as the thresholded portion appeared distinctly lighter in tone than the remainder of the unit on color aerial photography. It is very possible that the darker portion of this unit may represent a remnant of landform FtN (a unit composed of CL soils) (Myers, 1973). Unit FtML4 may therefore have been classified correctly.

The western portion of a meander scar (unit FoML4) was classified as CL soil, as was the eastern portion (unit FoCL4). Whether or not the classification of FoML4 is incorrect is uncertain. The labeling of this unit as an ML soil is based soley upon one "poorly placed" soil sample. The soil sample is situated dangerously close to an exposed sandy C horizon of unit FtN.

Soils of the large meander scar (unit FoCL3, in contact with I-24 (Old)) were partially misclassified, some parts being classified as CL soils, others as ML soils. This same unit was previously totally misclassified in terms of soil texture.

The only CH soil in the flightline, located within a glacial till area near the town of Oskaloosa, was mapped very well. The only misclassification involving this spectral class of soil occurred in two small portions of Newman terrace (FtN and FN) where Newman (CL) soils were confused with glacial (CH) soils.

OH soils, occurring in a very narrow meander scar (unit Fo (CL-OH) 4, Figure 4a), were also mapped very well. CL soils within a young flood terrace near the town of Oskaloosa were, however, misclassified as OH soils.

Development of a Technique For Engineering Soils Mapping Using Computer-Assisted Remote Sensing Techniques

Results of this study indicate that, under geographic and atmospheric conditions similar to those encountered in this study, engineering soils mapping can be accomplished through computer-assisted analysis of remote sensing data. This analysis would not consist solely of a "nonsupervised" or "supervised" approach, but would instead consist of a blend of the two approaches. The following data analysis sequence is suggested:

1) location of known cultural features through visual examination of multispectral image tones--researcher becomes more familiar with the imagery and can locate ground truth areas within it;

2) production of a generalized bare soil-vegatation-water map through clustering (nonsupervised) techniques--a maximum of four wavelength bands should be employed (preferably two in the visible portion of the spectrum and two in the reflective infrared);

3) manual (supervised) selection of significant soil fields (based on ground truth information, etc.) from soil cluster classes for use in training the computer; and

4) classification of the entire test site using the selected training fields and subsequent evaluation based upon known conditions.

DISCUSSION OF RESULTS

An attempt was made in this study to map soil types through automatic and semi-automatic digital processing of airborne multispectral scanner data. A low degree of success was achieved in landform mapping using the automatic imagery analysis technique, while mapping of engineering soils using the semi-automatic data processing technique was moderately successful. It is felt that the success in mapping engineering soil types was a direct result of the correlation between soil reflectance and 1) landform type, 2) soil texture, and

3) engineering soil subgroups of the Unified Soil Classification System (ML, CL, CH, and OH soils).

Soil texture was found to best correlate with soil spectral classes. That is, those engineering soil map units which differed significantly in soil texture did, in most cases, differ significantly in their spectral signatures.

Selected Unified Soil Classification System subgroups were found to correlate with soil spectral classes moderately well. Most computer mapping errors were confined to areas of ML soils (inorganic silts and fine sands).

Correlation of landform types with soil spectral classes was poor in both the nonsupervised and supervised analyses. This is extremely unfortunate, as landform units are often mapped as indicators of engineering soil types. Those landform types that did correlate well were those exhibiting unusually bright or dark spectral signatures.

Unfortunately, the success reported here in mapping soil textural groups may be fortuitous. That is, differences in soil spectral response within the study area may not be directly due to differences in soil texture. Observations by Myers (1973) and by Rowland (1973) indicate that a direct relationship may exist between soil texture and soil organic matter content in the alluvial portion of the study area. It appears that the finer the soil texture, the higher the soil organic matter content. This would explain why the spectral response of alluvial soils in the test site decreases with increasing clay contents (effect seen by the writer during analysis of spectral response graphs and by Stallard and Myers (1972) during analysis of spectroradiometer data).

The possibility that different levels of soil organic matter were responsible for the writer's success in mapping gross soil textural groups is strengthened by studies done by Horvath et al. (1971) and Al-Abbas et al. (1971). Both of these research teams have found the 1.5 to 1.8 micrometer wavelength band to be extremely useful in their attempts to map soil organic matter levels using automatic data processing of airborne multispectral scanner imagery; this same wavelength band appeared in all "best" sets of four and six wavelength band combinations involved in the writer's study.

Although results of this research indicate a potential for computer-assisted mapping of engineering soil types, this potential may not be realized under atmospheric or geographic conditions different from those present in this study. In order that this problem be dealt with properly, it is recommended that a determination be made of:

1) where (in the U.S.A. or the world) and to what degree soil organic matter, color, moisture, and texture influence the spectral properties of soil; and

2) for the same areas, if and to what extent a correlation exists between soil texture and Unified Soil Classification System subgroups.

And finally, regarding the merits of supervised and nonsupervised approaches to computer mapping of earth materials, the following observations are drawn from this study.

1) The nonsupervised classification technique applied to engineering soils mapping demonstrated the following advantages over the supervised technique:
   a) involved fewer man-hours (not necessarily fewer computer-hours), less human intervention, and less bias than the supervised technique.
   b) provided for selection of training samples that were more fully representative of an entire soil class (or map unit).

2) The supervised classification technique demonstrated one distinct advan-

tage--it provided greater detail and accuracy in the mapping of engineering soil types than did the nonsupervised technique.

3) Using the supervised approach, some engineering soil types can be classified based on training samples located at considerable distance (up to 10 km. in this study) from the area classified (single overflight assumed).

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