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Mapping Soil Features from Multispectral Scanner Data

BY S. J. KRISTOF AND A. L. ZACHARY

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Abstract

In being able to identify quickly gross variations in soil features, the computer-aided classification of multi-spectral scanner data can be an effective aid to soil surveying. Variations in soil tone are easily seen as well as variations in features related to soil tone, e.g., drainage patterns and organic matter content. Changes in surface texture also affect the reflectance properties of soils. Since conventional soil classes are based on both surface and subsurface soil characteristics, the technique described here can be expected only to augment and not replace traditional soil mapping.

Introduction

The use of multispectral remote sensing in conjunction with computer analysis techniques for soil studies has previously been reported by Kristof (2). His results showed that this new technology can be used to "map" some soil surface conditions over small areas with a reasonable degree of accuracy.

This type of computer-aided classification is based primarily on soil spectral variations (1). The approach involves subjective selection of a set of reference or "training" samples from a computer generated gray-level display of spectral variations. Each resolution element is then classified using a maximum likelihood ratio. Output is a computer printout which identifies each class with a different symbol.

In order to determine the usefulness of this type of automatic classification method, it is necessary to take a closer look at the yardstick often used to evaluate it: the conventional soil maps which delineate soils on the basis of morphology - color, structure, texture, etc. What can be reasonably expected of a system dependent on spectral response as the major input data? For example, should one expect a computer classification based on surface spectral properties to discriminate soils which have a fragipan (3) from those which do not since this feature occurs below the soil surface? Secondly, can a system based on individual analyses of a great number of resolution elements be

expected to reflect the clearly-defined soil boundaries of soil maps, a delineation which, in not recognizing the presence of transitional soils, to an extent ignores the reality of the situation?

The research reported here was conducted to augment the preliminary studies previously reported in the Journal of Soil and Water Conservation (2) and to seek to point out the inevitable limitations that arise if one demands that this type of data analysis create "maps" that correspond to conventional soil maps.

Study Areas

Four soil test areas were designated for this study. Two of the areas are located in the central part of Indiana in Morgan County near the West Fork of the White River. Designated as Soil Test Areas 2 and 3 (STA 2 and STA 3), these two areas are located about 2 1/2 miles apart. The soils were developed in late Wisconsin glacial material including glacial till, outwash, and aeolian soils. The soils belong to the Alfisol soil order (Gray-Brown Podzolic) and Mollisol soil order (Humic Gley and Alluvial) (3). The topography of this area is from nearly level to rolling.

The other two study areas are located in Tippecanoe County, Indiana and were designated as Soil Test Areas 4 and 5 (STA 4 and STA 5). Soils in STA 4 are within the region of the Alfisols but include some wet Mollisols. These soils were developed in 18 to 36 inches of silt overlying glacial till. The topography is level to sloping. Soil Test Area 5 is also within the Alfisol

region but includes some wet Mollisols. The topography is nearly level. The soils in the southern half of STA 5 were developed in glacial till with less than 16 inches of silt at the surface, whereas the soils of the northern half were developed in deeper silts.

Procedures

Multispectral data from STA 2 and STA 3 were collected on April 28, 1967 by an airborne scanning spectrometer. Data were taken from an altitude of 4000 feet at approximately 1100 hours. Twelve wavelength bands were used in the computer analysis: 0.40-0.44, 0.44-0.46, 0.46-0.48, 0.48-0.50, 0.50-0.52, 0.52-0.55, 0.55-0.58, 0.58-0.62, 0.62-0.66, 0.66-0.72, 0.72-0.80, and 0.80-1.00 μm .

The multispectral data over STA 4 and STA 5 were collected on May 26, 1969 at approximately 1200 hours. The aircraft altitude was 4000 feet above the terrain. Eleven wavelength bands were used in the analysis: six in the visible portion of the spectrum (0.40-0.44, 0.52-0.55, 0.55-0.58, 0.58-0.62, 0.62-0.66, and 0.66-0.72 μm) and five in the infrared (0.72-0.80, 0.80-1.00, 1.00-1.40, 1.50-1.80, and 2.00-2.60 μm).

Spectral data from the four test areas were classified using computer-implemented pattern recognition techniques. Reference or training samples were selected on the basis of a conventional soil survey map and were used to classify the remaining part of the soil test area. Additionally, STA 3 was classified using training samples from STA 2 and vice versa. Similar reciprocal

classifications were conducted for STA 4 and STA 5 and for an area adjacent to STA 4.

Samples were taken from each of the several soil series represented and the average relative spectral response in each wavelength band was computed. The average relative spectral response in various combinations of wavelength bands was also computed for representative areas within each mapped soil series. Additionally, a ratio (V/IR) was computed as the average relative spectral response in the visible wavelengths divided by the average relative spectral response in the reflective IR wavelengths. These ratios and averages were evaluated as to their usefulness in discriminating the various soil types mapped. Relationships of these measurements to internal drainage characteristics, organic matter content, and color were investigated. Organic matter content and color were determined on surface soil samples collected only from STA 4 and STA 5. Computer "maps" produced by these various procedures were evaluated with respect to their correlation with conventional soil survey maps.

Results

Soil Test Areas 2 and 3

Figures 1 and 2 show a soil survey map and a computer classification, respectively, of STA 3. In most areas the computer printout compares favorably with the soil survey map. Light colored soils such as Princeton fine sandy loam and Martinsville

loam were assigned low density computer symbols ".", "-", "/", "=", and "I". The moderately dark Fox loam was assigned the symbol "H", and the dark colored soils, Rensselaer fine sandy loam and Ross loam, were assigned the symbols "M" and "Z". Vegetation, water, roads, and other non-soil ground targets were left blank on the printouts.

Figures 3 and 4 show a soil survey map and a computer classification, respectively, of the soils of STA 2. In this example, the computer classification was made using training samples from STA 3, about 2 1/2 miles away. In using this procedure some of the soil areas were thresholded, that is, were left blank on the printout, since the multispectral responses of the soils in the thresholded areas were not similar to the response of any soil in the STA 3 training samples. Some of the Martinsville loam in STA 2 was erroneously classified as Princeton fine sandy loam, and much of the Princeton soil in STA 2 was thresholded. This failure to classify is not illogical since the classification was based on spectral similarity to the reference samples. As seen in Table 1, the Princeton fine sandy loam in STA 2 has a much higher average relative response than any of the reference samples in STA 3. Some of the differences in reflectance between the Princeton soils in the two areas can be attributed to textural variations, those in STA 2 being much more eroded and hence having a higher chroma than the Princeton soils

TABLE 1. AVERAGE RELATIVE SPECTRAL RESPONSE AND COMPUTED RATIO (V/IR) FOR REPRESENTATIVE SAMPLES OF EACH SOIL TYPE IN VISIBLE AND REFLECTIVE INFRARED WAVELENGTH BANDS.

<u>Soil Types</u>	<u>Visible Wavelengths (0.40-0.72μm)</u>	<u>Infrared Wavelengths (0.72-1.00μm)</u>	<u>Ratio (V/IR)*</u>
<u>STA 2</u>			
Princeton fine sandy loam	131.32	89.47	1.47
Martinsville loam	90.37	73.76	1.23
Fox loam	83.05	68.57	1.21
<u>STA 3</u>			
Princeton fine sandy loam	94.98	76.57	1.24
Martinsville loam	87.84	72.22	1.22
Fox loam	76.07	62.95	1.21
Ockley loam	85.57	71.52	1.20
Miami loam	79.74	67.86	1.18
Ross silt loam	73.06	62.25	1.17
Crosby loam	83.87	72.85	1.15
Rensselaer fine sandy loam	66.53	56.91	1.17

*The ratio (V/IR) is defined as the average relative spectral response of an object in the visible portion of electromagnetic spectrum divided by the average relative response in the reflective infrared portion of the spectrum.

in STA 3. The measurements for Martinsville loam and for Fox loam were similar in both areas, but the soils were nevertheless incorrectly classified. This could be due to several things: variations in surface moisture, differences in erosion of the two areas, surface roughness, organic matter content as well as variations in instrumentation, scanner calibration, sun angle, etc.

Soil Test Areas 4 and 5

Figures 5 and 6 show a soil survey map and a computer classification, respectively, of STA 4 and an area adjacent to STA 4. There is reasonably good agreement between the soil survey map and the computer "map". The separation of light soils from dark ones was accomplished with some dependability, and within the dark soils the classification of Kokomo and Brookston soils was quite successful. The separation of two light soils, Xenia and Russell, was not successful. Although these two soils have similar surface colors, they differ in subsurface drainage characteristics. The additional infrared wavelength bands used in collecting data over STA 4 and 5 made no significant contribution to classification accuracy.

Figures 7 and 8 are a soil survey map and a computer classification, respectively, of STA 5. Here again, reasonably good agreement was obtained, especially for Ragsdale and Reeseville soils.

While much of the Brookston soil was "mapped" by the computer as Ragsdale, the color similarity of the two soils can account for this confusion. It is important to note that the chief differences between Ragsdale and Brookston soils lie in the texture of the subsoils; the Ragsdale soils were developed in silt and have a surface texture of silt loam or silty clay loam, whereas the Brookston soils were developed from glacial till with or without a thin loess cap, and their surface textures may be silt loam, silty clay loam or clay loam. The two soils are, however, of similar color. Analogous errors arose in the classification of Celina and Crosby soils, with some Celina and Crosby areas being misclassified as Reeseville. Crosby and Reeseville soils have similar surface color and the same drainage characteristics, but, while Reeseville soils are developed in loess, Crosby soils are developed mostly in glacial till, with or without a thin loess cover. Celina, Crosby and Reeseville soils have similar color designations on the Munsell charts.

Tables 2 and 3 are important in evaluating the results of the classifications of STA 4 and STA 5. As shown in Table 2, the only soils common to the two areas are Brookston silty clay loam and Toronto silt loam, and, while the drainage characteristics of each soil type are the same in both areas, there are slight variations in organic matter and color within a single soil type from one area to the next. The spectral responses of the soils in STA 4 and STA 5 are shown in Table 3. It is interesting to

TABLE 2. DESCRIPTIVE INFORMATION FOR SOIL SERIES OF STA 4 and STA 5.

<u>Soil Type</u>	<u>Internal Drainage Class of Soil Series</u>	<u>Average Percent Organic Matter of Soil Samples</u>	<u>Typical Color of Moist Soil Samples (Munsell Charts)</u>
<u>STA 4</u>			
Kokomo silty clay loam	Very poorly drained	4.25	10YR 2/1
Brookston silty clay loam	Very poorly drained	4.00	10YR 2/1
Toronto silt loam	Somewhat poorly drained	2.19	10YR 3/1
Metea silt loam	Well drained	2.35	10YR 4/2
Del Rey silt loam	Somewhat poorly drained	1.70	10YR 4/2
Fincastle silt loam	Somewhat poorly drained	1.62	10YR 4/2
Xenia silt loam	Well drained	1.36	10YR 4/2
Russell silt loam	Well drained	1.65	10YR 4/3
<u>STA 5</u>			
Ragsdale silty clay loam	Very poorly drained	4.20	10YR 2/2
Brookston silt loam	Very poorly drained	3.38	10YR 2.5/1.5
Brookston silty clay loam	Very poorly drained	4.07	10YR 2.5/1
Toronto silt loam	Somewhat poorly drained	2.80	10YR 3/1
Crosby silt loam	Somewhat poorly drained	1.80	10YR 4/2
Celina silt loam	Moderately well drained	1.60	10YR 4/2
Reeseville silt loam	Somewhat poorly drained	1.96	10YR 4/2

TABLE 3. AVERAGE RELATIVE SPECTRAL RESPONSE AND COMPUTED RATIO
(V/IR) FOR REPRESENTATIVE SAMPLES OF EACH SOIL TYPE IN
VISIBLE AND REFLECTIVE INFRARED WAVELENGTH BANDS.

<u>Soil Types</u>	<u>Visible Wavelengths (0.40-0.72μm)</u>	<u>Infrared Wavelengths (0.72-2.60μm)</u>	<u>Ratio (V/IR)</u>
<u>STA 4</u>			
Russell silt loam	141.21	137.64	1.026
Fincastle silt loam	142.60	134.74	1.058
Xenia silt loam	137.15	133.08	1.031
Metea sandy loam	125.80	124.27	1.012
Del Rey silt loam	107.94	105.80	1.020
Toronto silt loam	102.10	107.48	0.950
Brookston silty clay loam	84.94	91.28	0.931
Kokomo silty clay loam	82.93	87.97	0.943
<u>STA 5</u>			
Reeseville silt loam	115.73	108.48	1.067
Crosby silt loam	110.76	107.14	1.033
Celina silt loam	105.25	103.46	1.017
Toronto silt loam	103.53	107.16	0.966
Brookston silt loam	93.25	98.72	0.944
Brookston silty clay loam	82.10	87.04	0.943
Ragsdale silty clay loam	78.76	85.10	0.925

note that even though color and organic matter differ slightly within a given soil type, the reflectance in both the visible and infrared wavelengths was quite similar and, hence, the computed ratio (V/IR) for the samples.

Even though there were just two soil types common to STA 4 and 5, the attempt was made to classify STA 4 and an area adjacent to STA 4 using training samples from STA 5 (Figure 9). In general, the Brookston soil in the area adjacent to STA 4 was correctly classified by this method, but the Toronto soil of STA 4 was incorrectly classified as Brookston. Since other soils in STA 4 and the adjacent area were not common to both areas, the separations that were made were related to color and organic matter content as shown in Table 2.

Figure 10 shows a classification of STA 5 using training samples from STA 4. The light and dark soils were distinguished from one another, but much of the Brookston soil and Toronto soil was "mapped" by the computer as Kokomo rather than Brookston. Most of the Reeseville area was "mapped" as Fincastle; this result is quite logical since the Reeseville and Fincastle series are similar in most respects, including surface color and texture.

Conclusions

"Mapping" of soil features using multispectral scanner data and computer-implemented pattern recognition techniques was partially successful. Since soil series are conventionally differentiated by both surface and subsurface properties, they cannot

be expected to have observable surface differences in all cases. Further difficulty was encountered when attempting to "map" a soil series (or soil type) in one soil test area using training samples from another soil test area located at a distance of a few miles from the first. These difficulties could have been due to differences in illumination at the two soil test areas, differences in surface roughness, surface texture, or surface color, adjustments in instrumentation during data collection, or other factors. Since any given soil series has, by definition, an allowable range of surface conditions, it is inevitable that some spectral variations will occur within a soil series. The best identification and discrimination of soil series seemed to result when these variations within soil series were much smaller than variations between soil series. In some instances, the spectral variations within series were greater than between series.

A computed value for the average relative spectral response was useful in predicting how well the "mapping" of soil series could be accomplished. A ratio of visible to infrared response appeared to have additional utility in characterizing the spectral properties of soils.

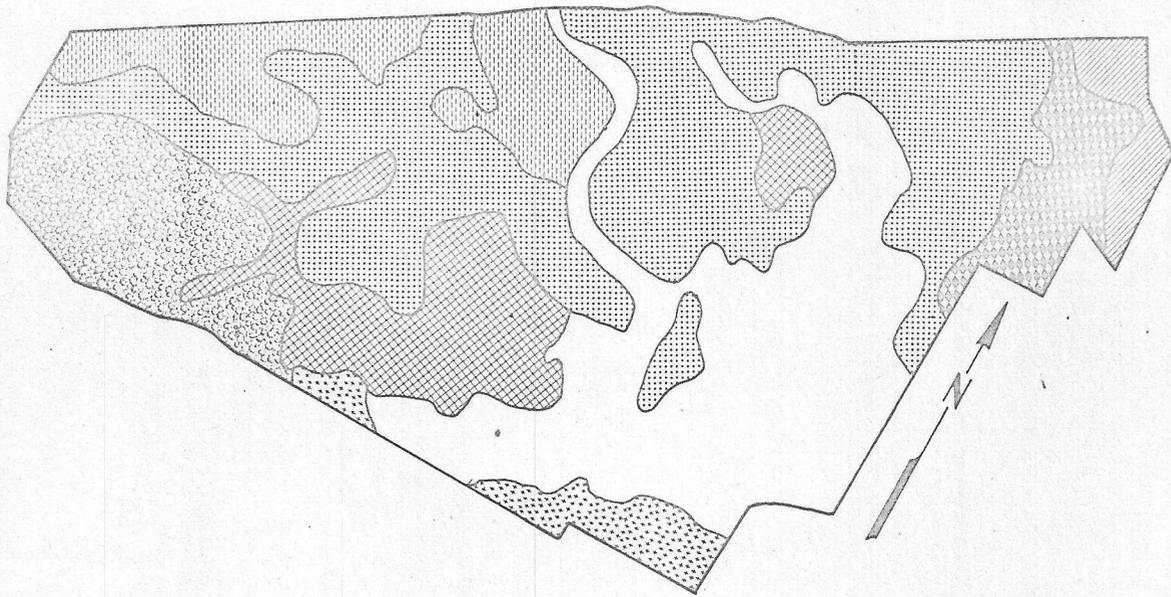
The promise of soil feature mapping using multispectral scanner data and computer-aided classification techniques lies not so much in the ability to achieve a one-to-one relationship with the categories of the traditional soil survey classification as in identifying grosser divisions of soils over very wide

areas in a short time. With this capability the technique can join with traditional soil survey techniques and photo-interpretation to help accomplish efficiently what no single method can accomplish alone.

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2. Kristof, S. J. 1971. *Preliminary multispectral studies of soils*. Soil and water conservation. Volume 26, Number 1. p. 15-18.
3. Soil Survey Staff. 1960. *Soil Classification, a comprehensive system: 7th approximation*. Washington, D. C.: U.S. Government Printing Office. 265 p.

- Figure 1. Soil Survey Map of STA 3.
- Figure 2. Computer Classification of STA 3.
- Figure 3. Soil Survey Map of STA 2.
- Figure 4. Computer Classification of STA 2.
- Figure 5. Soil Survey Map of STA 4 and Area West of STA 4.
- Figure 6. Computer Classification of STA 4 and Area West
of STA 4.
- Figure 7. Soil Survey Map of STA 5.
- Figure 8. Computer Classification of STA 5.
- Figure 9. Computer Classification of STA 4 Using Training
Samples of STA 5.
- Figure 10. Computer Classification of STA 5 Using Training
Samples of STA 4.



 Crosby I
 Miami I
 Ockley
 Princeton fsl

 Martinsville I
 Fox I
 Ross sil
 Rensselear fsl

2

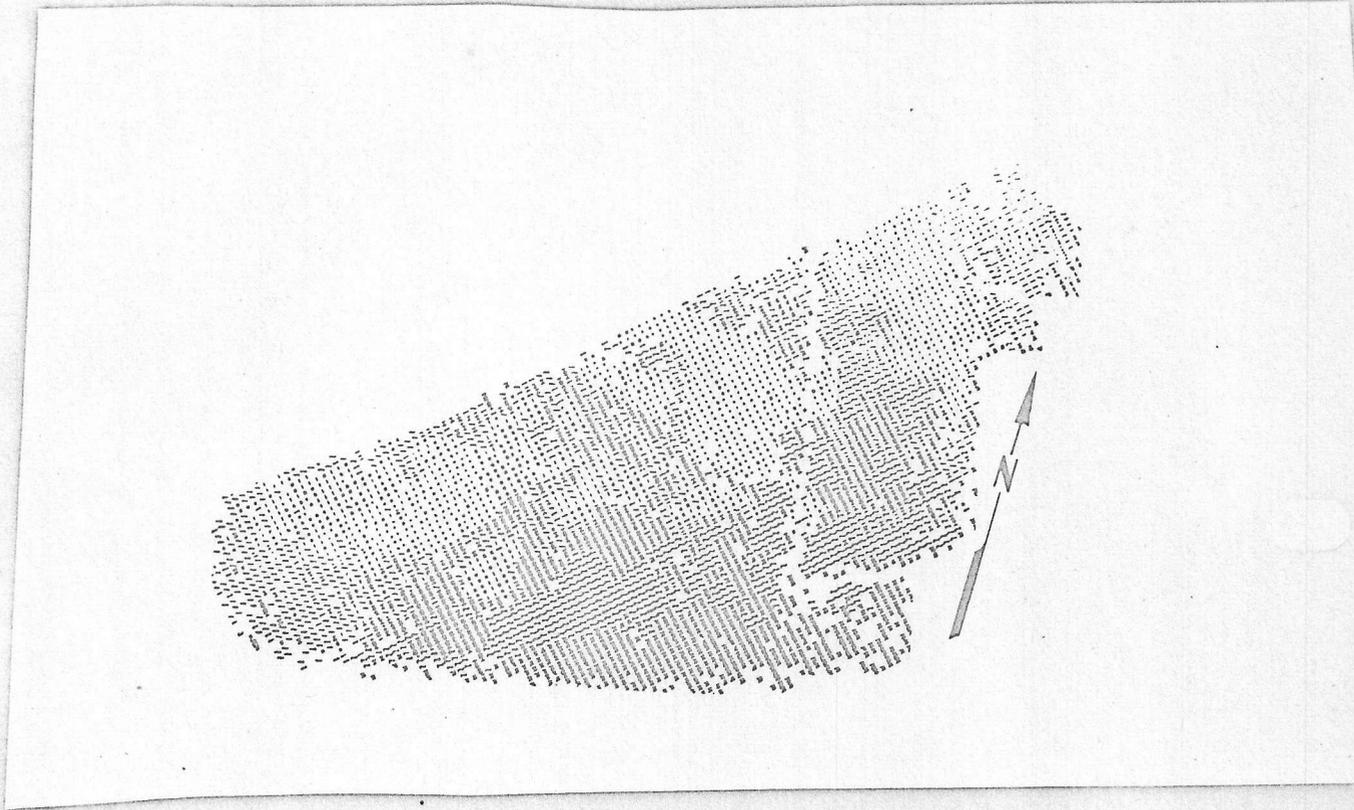
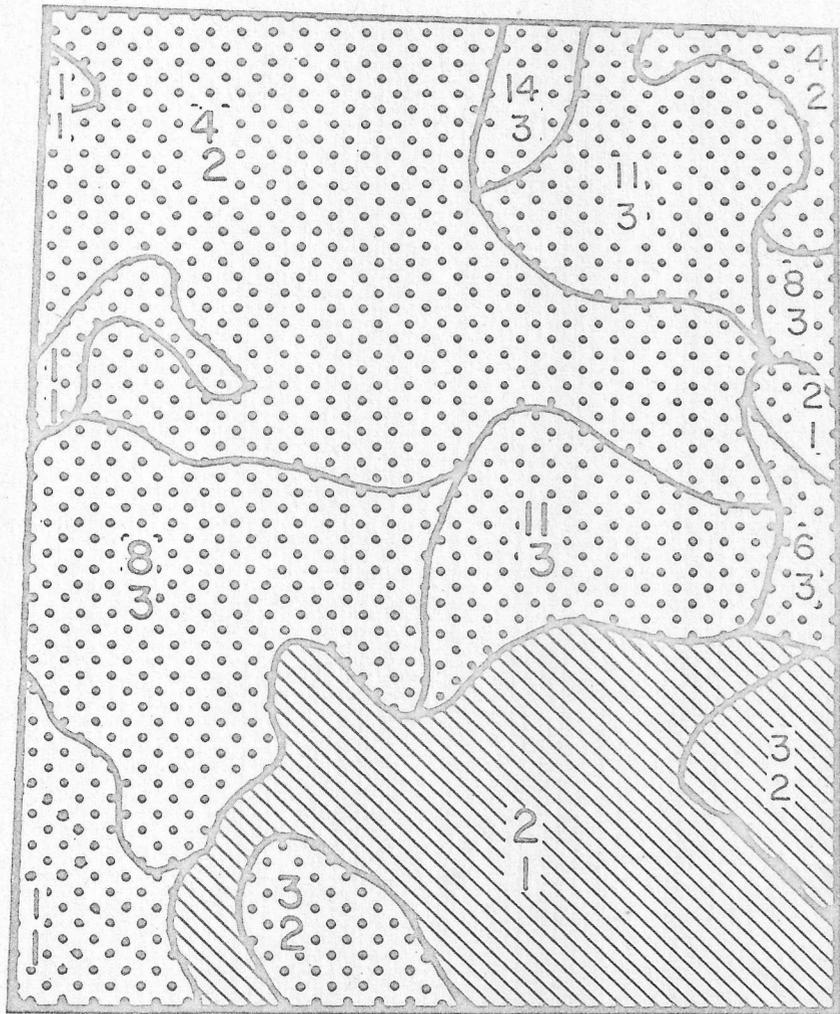


Figure 2

LEGEND:

- . Princeton fine sandy loam
- Martinsville loam
- / Ockley loam
- = Miami loam

- I Crosby loam
- H Fox loam
- M Rensselaer fine sandy loam
- Z Ross loam



Princeton fsl



Martinsville l

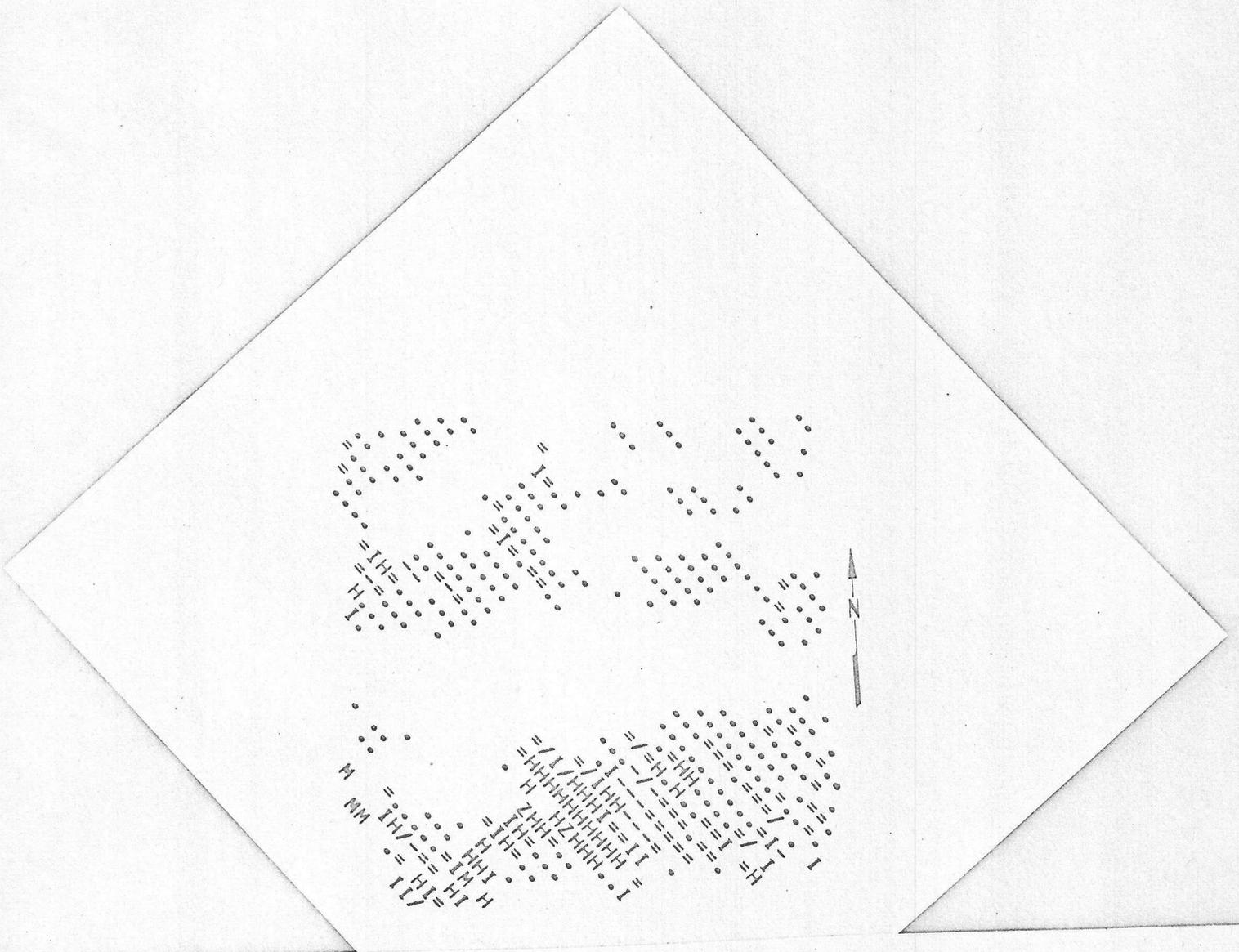
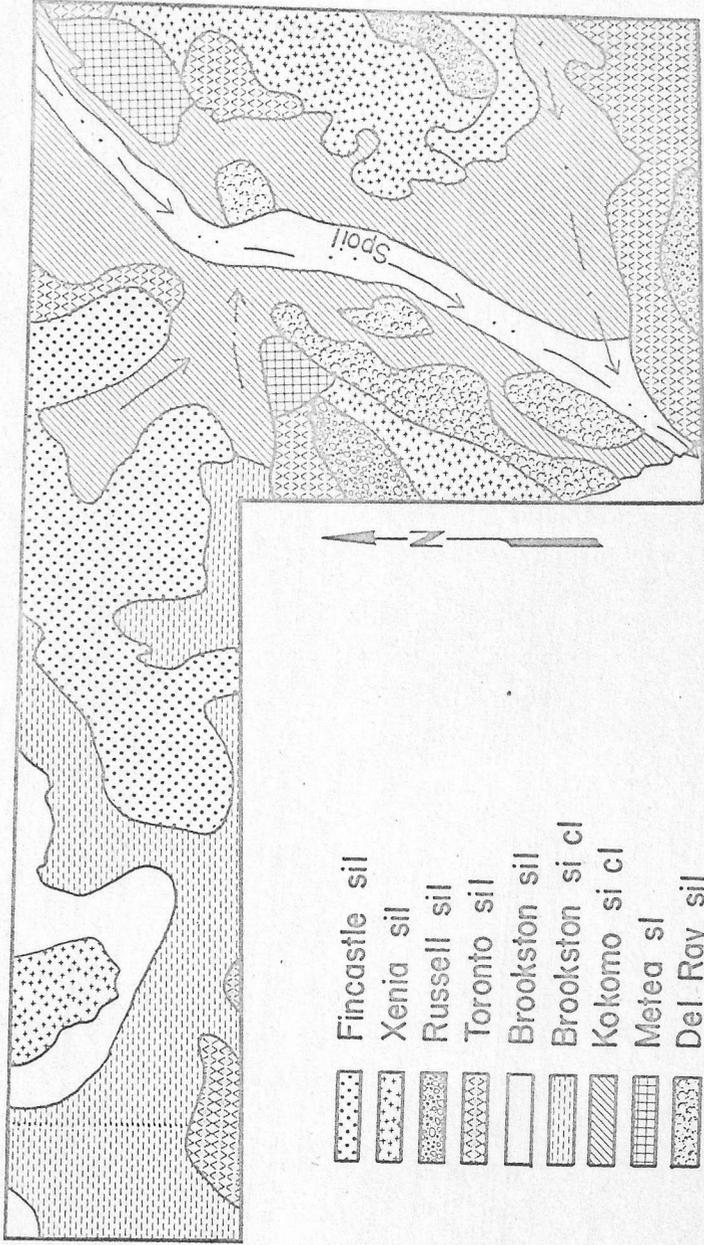


Figure 4

LEGEND:

- | | | | |
|---|---------------------------|---|----------------------------|
| . | Princeton fine sandy loam | I | Crosby loam |
| - | Martinsville loam | H | Fox loam |
| / | Ockley loam | M | Rensselaer fine sandy loam |
| = | Miami loam | Z | Ross loam |



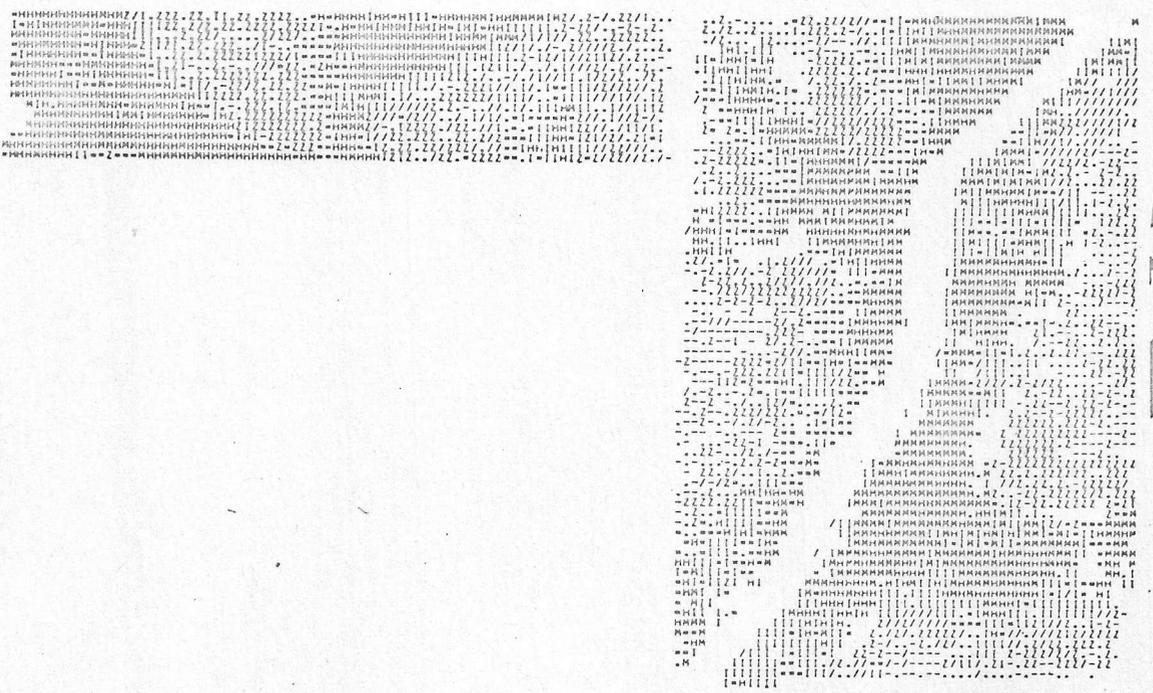
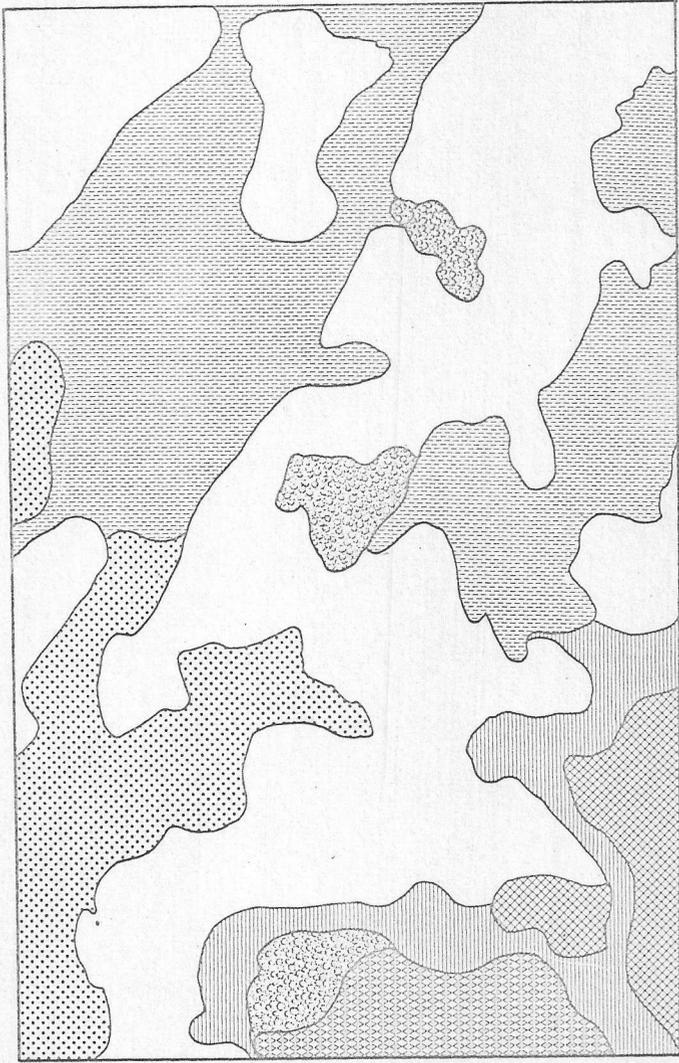


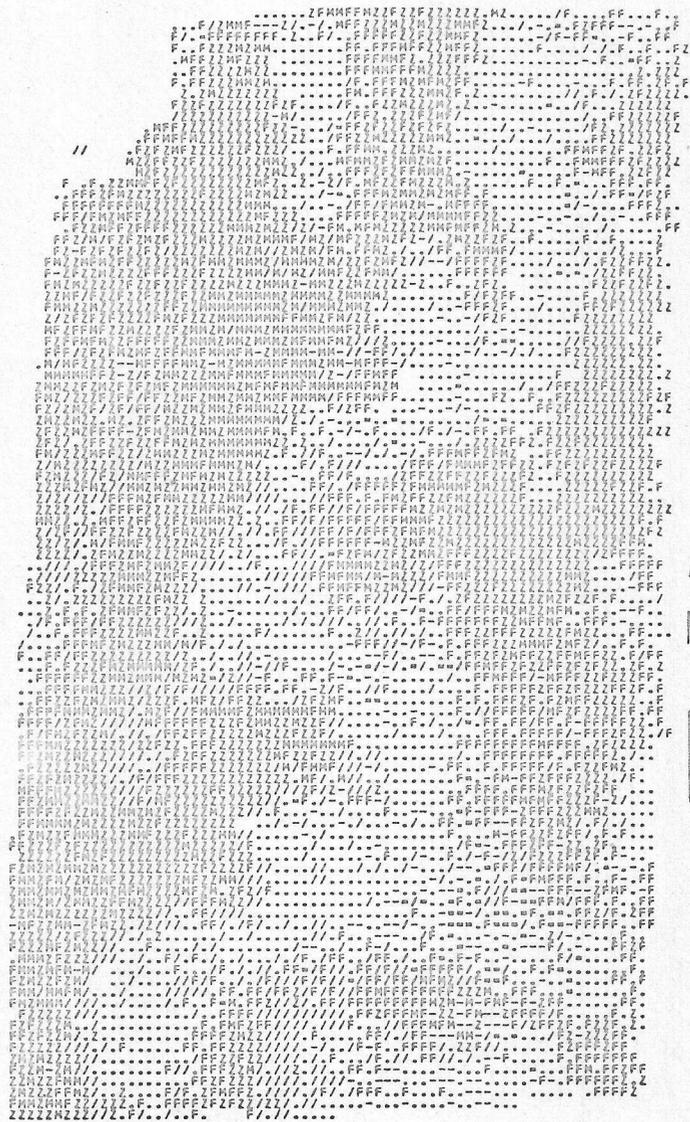
Figure 6

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 Ray silt loam



- | | |
|--|---|
|  Ragsdale sil |  Toronto sil |
|  Brookston sil |  Crosby sil |
|  Brookston sil |  Celina sil |
|  Reeseville sil | |



TRAINING CLASS SYMBOLS

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

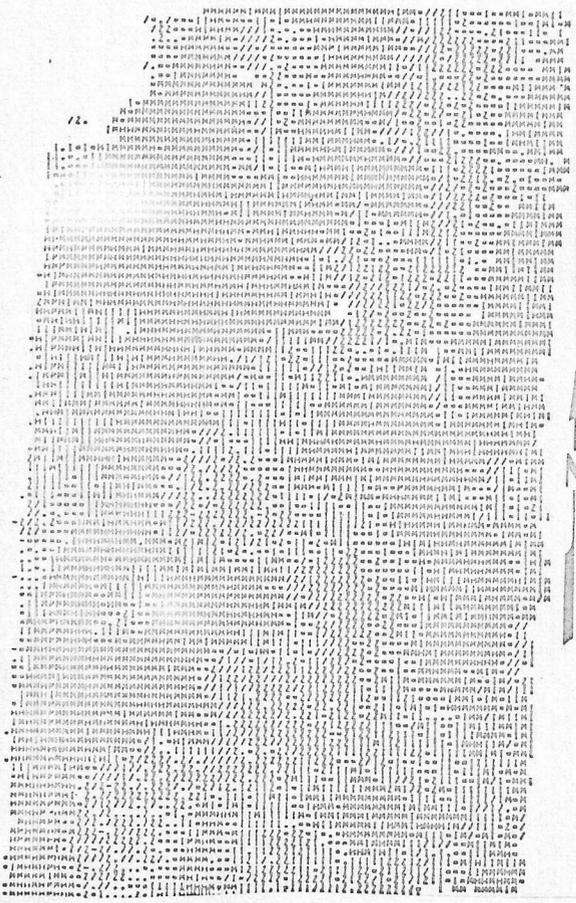


Figure 10

TRAINING CLASS SYMBOLS

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

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