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SECTION 47

DIFFERENTIATING ELEMENTS OF THE SOIL-VEGETATION COMPLEX*

by

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One of the most exciting prospects in the application of remote sensing technology is that of identifying, characterizing, measuring, and mapping different elements of the soil-vegetation complex. Important elements in this complex include soil properties, plant species, and the conditions of both soils and plants.

One of the problems in the use of remote sensing to study the soil-vegetation complex is the quantification and precise location of ground observation data such that it can be correlated with multispectral data acquired from aerospace platforms. A technique which has been found to be very effective in relating precisely these two sources of data involves the gridding and sampling of an area to be studied such that the exact location where soil or plant samples are obtained can be related precisely to a known address on a magnetic tape containing multispectral scanner data of the area. Once this has been accomplished, analytical data (ground observations) of each soil or plant sample from a specific grid point can be examined and related to quantitative multispectral data from an airborne scanner corresponding to the appropriate address or location on the magnetic tape.

For the past two years this approach has been used at Purdue University to determine if a correlation exists between the multispectral characteristics of a resolution element or scene and various physicochemical parameters within the soil-vegetation complex of that scene. These techniques were used in a study of soils and crops in a 60-hectare field in Tippecanoe County, Indiana (Figure 1). This area known as Soil Test Area 6 (STA 6), is made up of soils formed under tall prairie grass vegetation. A comparison of the photograph (Figure 1a) with the soils map (Figure 1b) shows a close similarity of soils patterns.

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*In this paper, results from a number of studies are summarized; researchers are identified in the Acknowledgment section.

One of the soil parameters that correlated well with spectral response was organic matter content. The correlation coefficient between organic matter content and multispectral response for data from approximately 200 grid points was 0.70. Grid points with known organic matter contents were used as the training set for computer-implemented analysis of the multispectral data and for the generation of a spectral map of four levels or organic matter content (Figure 2)

Although the correlations between multispectral response and both extractable soil phosphorus and exchangeable soil potassium were low, distinct soil or spectral patterns, representing different levels of soil P and soil K, were produced when analytical values from the grid points were used as training sets to produce computer-implemented maps of soil phosphorus and soil potassium (Figure 3).

In 1970 the northern third of STA 6 was planted in corn and the southern two thirds in soybeans. Corn and soybean leaf samples were obtained at specific grid points in August, 1970, the day on which multispectral data were obtained by the University of Michigan aircraft scanner. Grid points where plant nutrient (N,P,K) contents were known were used as the training sets for computer-implemented analysis and mapping of plant nitrogen, plant phosphorus, and plant potassium (Figure 4). Spectral data were used to produce maps delineating three levels of N for corn and three levels of N for soybeans (Figure 4A); three levels of P for corn and three levels of P for soybeans (Figure 4B); and three levels of K for corn and two for soybeans (Figure 4C).

Although statistical analysis did not produce a high correlation between spectral data and plant content of N, P, and K, definite spectral patterns were produced. Before valid conclusions can be drawn from an experiment with dynamic systems, such as plant nutritional status, the experiment must be conducted over a number of years and under a variety of geographical, climatic, and environmental conditions. Plant nutritional and spectral response studies are continuing at LARS.

If it becomes possible to use remote sensing to characterize crop conditions through the growing season, crop yield prediction capabilities may be improved. A preliminary yield study was conducted in STA 6. Yield samples were obtained at specific grid points. Spectral data relating to different yield levels at the grid points were used as the training set for computer-implemented analysis and production of the corn yield map (Figure 5A) and the soybean yield map (Figure 5B). These results are preliminary and were conducted in a very limited area. Such studies must be conducted through several growing seasons and under a variety of conditions before it can conclusively be stated that yields can be related to multispectral response.

These studies opened up a number of very interesting problems. One of these relates to the mechanism or technique of gridding. How is a precise grid point located in the scanner data? Is this important? In the first attempt to match the analytical ground data from the array of grid points with spectral data from an array of addresses on the magnetic tape, the geometric distortion inherent in the scanner was not considered. In a second correlation analysis, geometric corrections were made which gave a much more precise matching of ground data points and addresses on the magnetic tape. Great improvements were achieved in the correlation coefficient values, in one case an improvement in r^2 from 0.38 to 0.72 in a study of the correlation between soil organic matter content and spectral response.

Another important question which has been considered is: What is the best array of spectral channels (or wavelengths) for measuring or mapping a particular surface feature? In response to this question a study was conducted to determine the best portion of the reflective spectrum for delineating different levels of soil organic matter by remote sensing techniques. Multispectral scanner data obtained in May 1969 and May 1970 over three soil test areas (STA 4, 5 and 6) were used in this study. Each of the soil test areas was gridded, and organic matter content was determined for the surface soil sample taken at each of the 500 grid points. The best channel (or wavelength band) or best array of channels of spectral data for estimating organic matter content was selected by two computer programs. One method is based on the stepwise regression principle; the other is a LARS- developed program for channel selection based on divergence (1). Data from thirteen spectral channels in the visible and reflective infrared regions of the electromagnetic spectrum were used (Table 1).

Based on previous experience in channel selection, channels 5, 7, 8, and 10 were chosen for a special study. Various combinations of these four channels have a significant effect on the correlation of reflectance with soil organic matter content (Table 2).

Horvath and Baumgardner (2) concluded from this study that:

1. There is a high correlation between soil reflectance and soil organic matter.

2. Selection and number of multispectral channels used had a profound influence on this correlation.

3. The best combination of three channels gave superior correlations over those of the best two channels.

4. In some cases four channels gave superior correlations over those of the best three channels; five or more channels seldom improve r^2 values over those obtained with three or four best channels.

5. There is no single best array of spectral channels for computer-implemented mapping of soil organic matter under a wide variety of conditions and locations.

A question closely related to that of channel selection is: What is the optimum size of training sets in order to obtain the best correlation between multispectral response and a particular parameter of an earth surface feature. In this case soil organic matter content was selected as the parameter to be used. For the limited area and conditions under which this study was conducted, it was found that increasing the size of the training set (the number of scanner resolution elements around each field grid point to be used to train the computer) up to an optimal size improved the correlation between reflectance and organic matter content (Table 3).

Roth and Baumgardner (3) concluded from this study that:

1. Training set size significantly affected correlation between soil reflectance and organic matter content.

2. Training sets used for computer-implemented analysis of multispectral data should consist of at least 36 scanner resolution elements for best correlation with soil analysis data.

One of the very promising applications of the techniques presented in this paper is in the inventorying and mapping of the soils resources of the world. Scientists at LARS are working with the Soil Conservation Service in Indiana to evaluate various remote sensing techniques as an aid in classification and mapping of soils. Recently spectral classifications of soils have been made from multispectral scanner data obtained in May 1971 over flightline 212 in Montgomery County, Indiana. The objective of this research is to find that combination of training data, training set size, array of spectral channels and other techniques which will produce the most meaningful and useful spectral classification or map of surface soils. It is the goal of the soil scientists at LARS to be able to put into the hands of the soil surveyor spectral maps which will greatly accelerate and improve the accuracy of soil surveying and mapping.

In the Montgomery County study fourteen spectral classes of soils were mapped by computer (Figures 6 and 7). In Figure 6 data from all twelve available reflective channels were used in the spectral classification. The classification results in Figure 7 were obtained with the analysis of data from the four best channels as selected by the divergence method (1). In this study it was found that the classification results are greatly affected by the method which is used to select the spectral classes. Where total reflective data were used as a basis for spectral class selection, the classification results gave indistinct class boundaries and much more complex spectral patterns (Figure 6A and 7A) than were achieved where only visible reflectance (Figures 6B and 7B) and only reflective infrared (Figures 6C and 7C) were used for spectral class selection.

Although fourteen spectral classes would seldom be meaningful and useful in delineating soil types in so small an area, this research provides a basis for better spectral classification. Further study is needed to assist in combining classes and select boundaries between spectral classes to generate a more usable product.

Scientists at Pennsylvania State University and Purdue University are cooperating in a project funded by the U.S. Department of Transportation (4). This project involves the analysis and interpretation of multispectral scanner data from a 47-mile flightline in southeastern Pennsylvania (Figure 8). Scanner data were obtained in May 1969 at a time of maximum bare soil exposure. Seven segments, each 3 to 5 miles in length and containing primarily one parent material were designated for study. Parent materials along the flightline include limestone, shale, sandstone, conglomerate, and perhaps others. To date, four of these segments have been studied in detail using pattern recognition techniques. Results indicate that parent materials can be mapped in the individual segments. Spectral mapping of surface soils has been done in the limestone area. Many of the soil features and patterns are easily seen in an aerial photograph (Figure 9). The patterns in the spectral map delineating three classes of soils and one class of green vegetation compare very well with the field survey map (Figure 10).

Plans for the Earth Resources Technology Satellite (ERTS) Experiment have captured the imagination and interest of people around the world. For many months investigators at LARS have been preparing and training for receiving, analyzing and interpreting earth resources data to be obtained from ERTS. Digitized data from the multichannel photography taken on March 12, 1969, as a part of the S065 Experiment of Apollo 9 have been used to simulate ERTS data. Digitization and analysis techniques have been described by Anuta and MacDonald (5).

One of the important agricultural regions in the U.S. which was photographed in the S065 Experiment is the Southern Great Plains Region around Lubbock, Texas (Figure 11). A general soils map of Crosby County, Texas, which occupies 911 square miles in the center of the Apollo 9 photograph, clearly illustrates the differences between the High Plains and the Rolling Plains (Figure 12). The White River and its many small tributaries are clearly seen in the eastern and southeastern portions of the map of Crosby County.

Without any ground identification of surface features other than those provided in a Soil Survey Report of Crosby County (6), a spectral analysis and classification were made of Crosby County, using the digitized 3-channel (2 visible, 1 infrared) photographic data (Figure 13). Many surface features are easily identifiable and separable with this spectral data. These include towns, highly reflective dry riverbeds, bodies of surface water, irregular spectral patterns associated with rangelands, and regular patterns associated with cultivated agricultural areas. Within the cultivated region many levels of spectral response are separable and mappable by pattern recognition techniques. Those fields having very high reflectance in the visible spectrum may be covered with residue from the previous crop of grain sorghum. Fields having very low reflectance may be wet, freshly plowed, or be covered with winter wheat. There also seem to be many fields with neither high nor low relative reflectance. The reflecting surfaces of such fields may contain cotton or grain sorghum residues which have been incorporated and mixed into the surface soil to varying degrees by different tillage operations.

The White River Reservoir, which serves as the muncipal water supply for Crosbyton, Texas, is located in the southeastern corner of Crosby County (Figure 14). The reservoir, the dry river channels, the random patterns of the surrounding rangelands, and the ordered shapes of the cultivated fields are easily discernible.

It is a simple operation to instruct the computer to print or map only those features of interest (Figure 15). This technique can delete superfluous data from the scene and can allow the investigator to observe and display only the desired data.

Remote sensing techniques hold great promise for man in differentiating elements of the soil-vegetation complex. There is much that man does not understand about the relationships between the many physical-chemical parameters and the energy which is radiating from the soil-vegetation complex. The results which have been presented in this paper give rise to great optimism in the search for better understanding and definitions of those relationships. And with this understanding will come the technology and capability to apply remote sensing and automatic data processing techniques to a better use of earth resources and the preservation and maintenance of the quality environment.

It is with great anticipation that scientists around the world look forward to receiving, analyzing, interpreting, and evaluating earth resources data from the ERTS and Skylab Experiments.

ACKNOWLEDGMENT

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2. Horvath, E.E. and M.F. Baumgardner, 1971. Multispectral remote sensing of soils, II. Optimum spectral wavelength for computer-implemented mapping of soil organic matter. Agronomy Abstracts, p. 99.

3. Roth, C.B. and M.F. Baumgardner, 1971. Multispectral remote sensing of soils, I. Optimum training set size for computer-implemented mapping of soil organic matter. Agronomy Abstracts, p. 105.

4. West, T.R., 1972. Engineering soils mapping from multispectral imagery using automatic classification techniques. Paper presented at 51st Annual Meeting of Highway Research Board.

5. Anuta, P.E. and R.B. MacDonald, 1971. Crop surveys from multiband satellite photography using digital techniques. Remote Sensing of Environment 2: 53-67.

6. Soil Survey, 1966. Crosby County, Texas. Soil Conservation Service, U.S. Department of Agriculture.

Table 1. Summary of Spectral Channel Selection

Conditions:
1. Data for 1969 and 1970
2. Data for 3 soil test areas
3. Channel selection made by 2 methods
4. Best 1, 2, and 3 channels selected

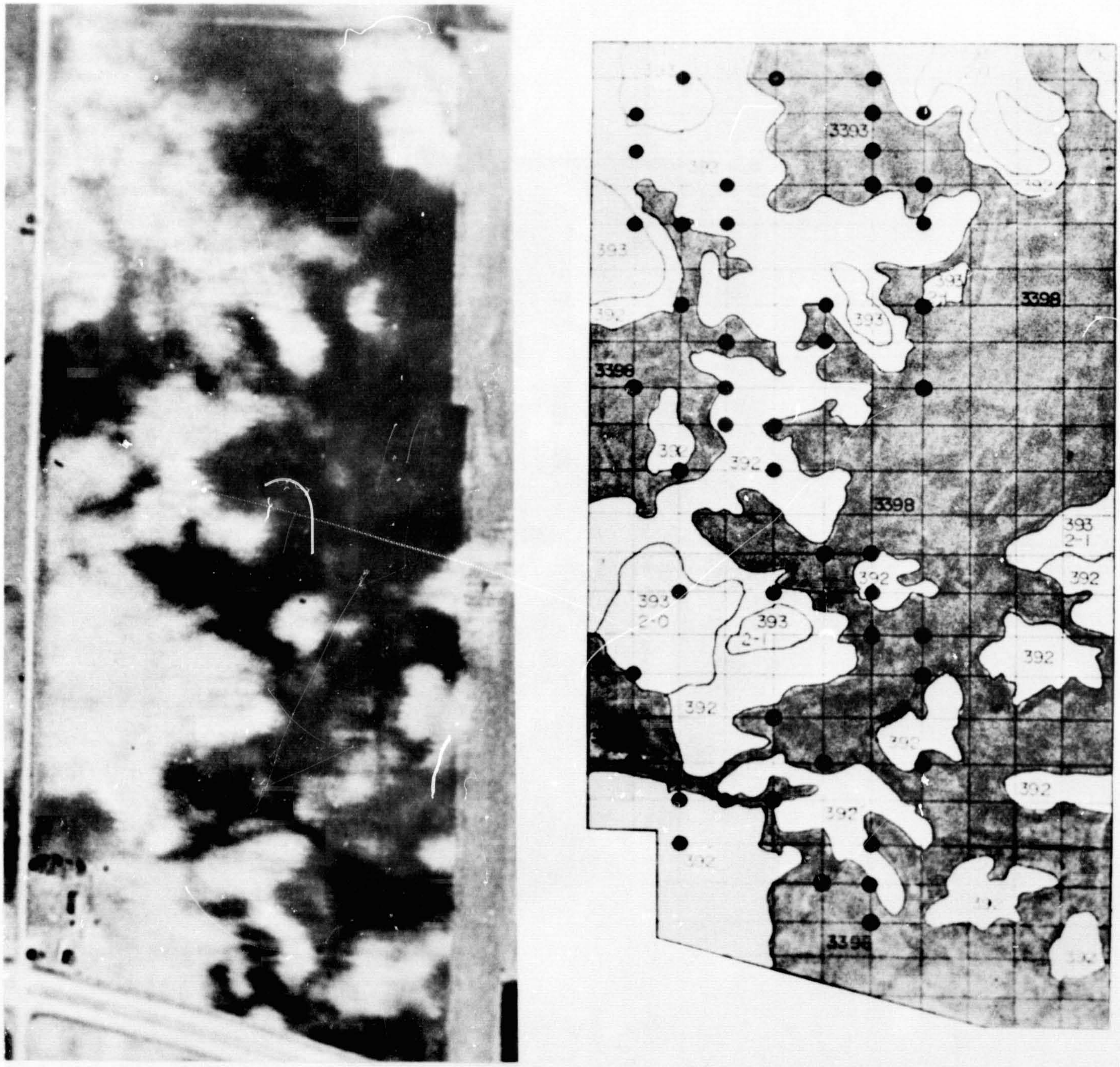
Channel No.	Wavelength (in μm)	Color	No. of Times Selected as Best Channel (12 possibilities)	No. of times selected among 1, 2, or 3 Best Channel (72 possibilities)
1	.40-.44	Violet	1	4
2	.46-.48	Blue	0	0
3	.50-.52	Blue-green	0	3
4	.52-.55	Green	1	1
5	.55-.58	Yellow	0	3
6	.58-.62	Orange	2	3
7	.62-.66	Red	2	12
8	.66-.72	Dark red	0	5
9	.72-.80	Reflective IR	1	4
10	.80-1.00	Reflective IR	3	9
11	1.00-1.40	Reflective IR	0	7
12	1.50-1.80	Reflective IR	0	5
13	2.00-2.60	Reflective IR	2	16

Table 2. Effect of spectral channels selected on the correlation of reflectance with soil organic matter

Channel Combinations	r^2 values
5,7,8,10	.69
5,7	.68
5,8	.60
7,10	.45
8,10	.45
7	.44
5	.38

Table 3. The effect of training set size on the correlation between soil reflectance and soil organic matter content (Channels 5 & 7)

Number of Resolution Elements	r^2 values
1	.52
4	.59
16	.64
36	.68
144	.69
722	.70



a. Aerial Photograph b. Soils map

Figure 1. Soil Test Area 6 in Tippecanoe County, Indiana.

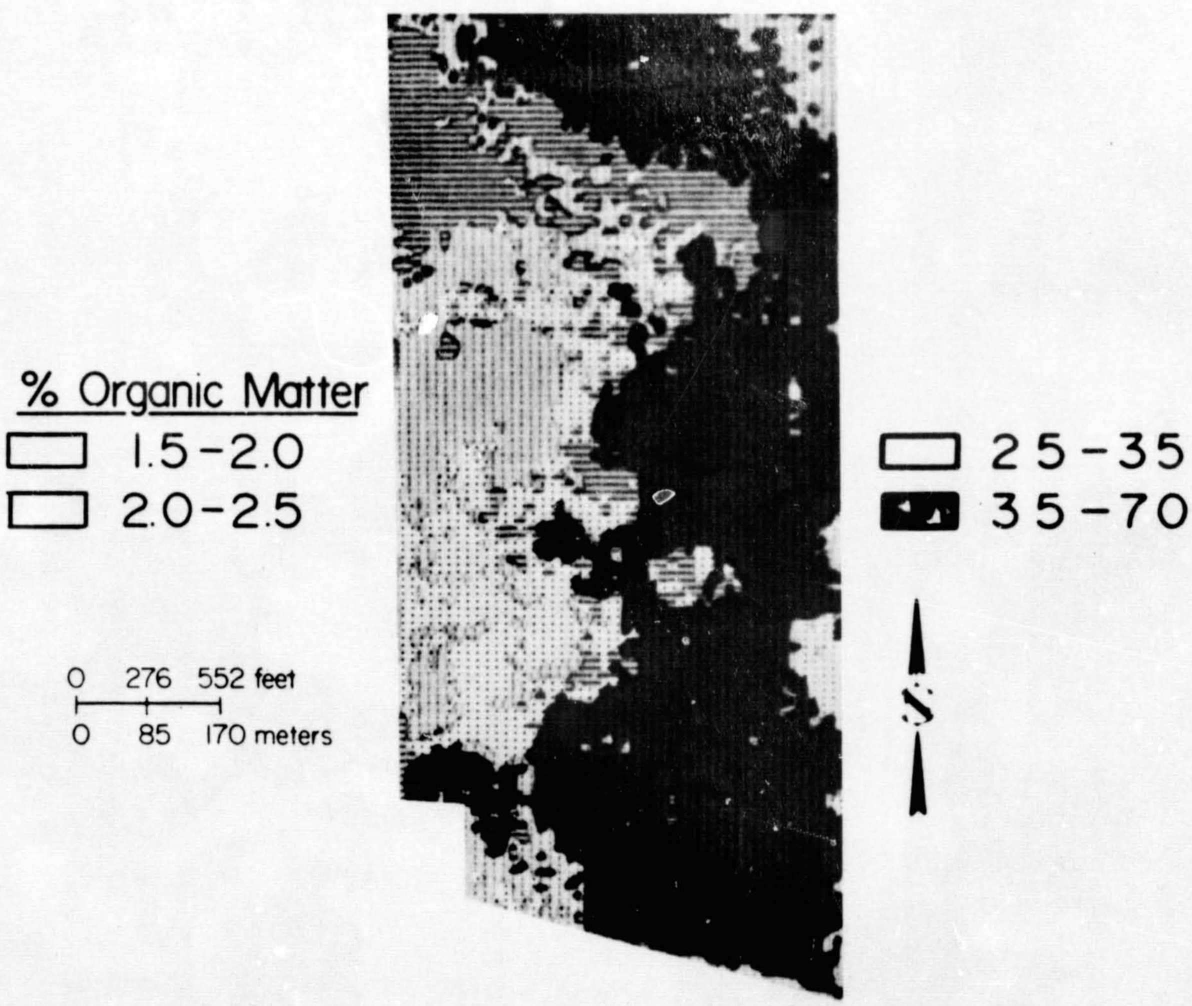
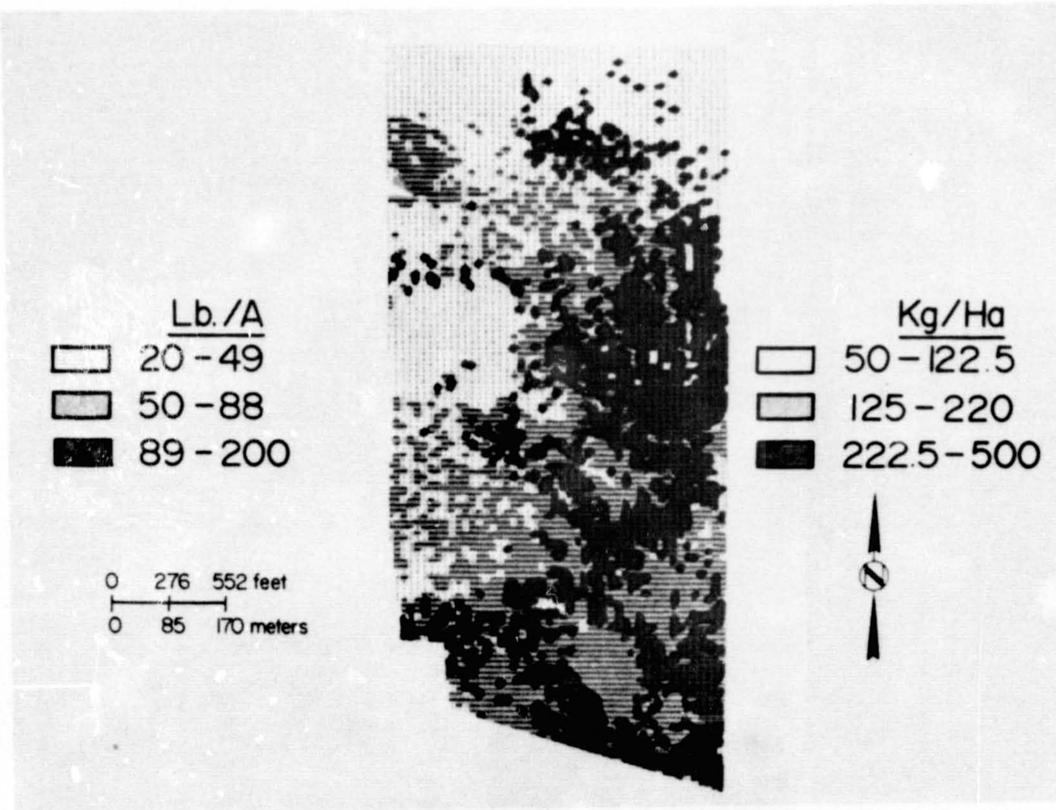
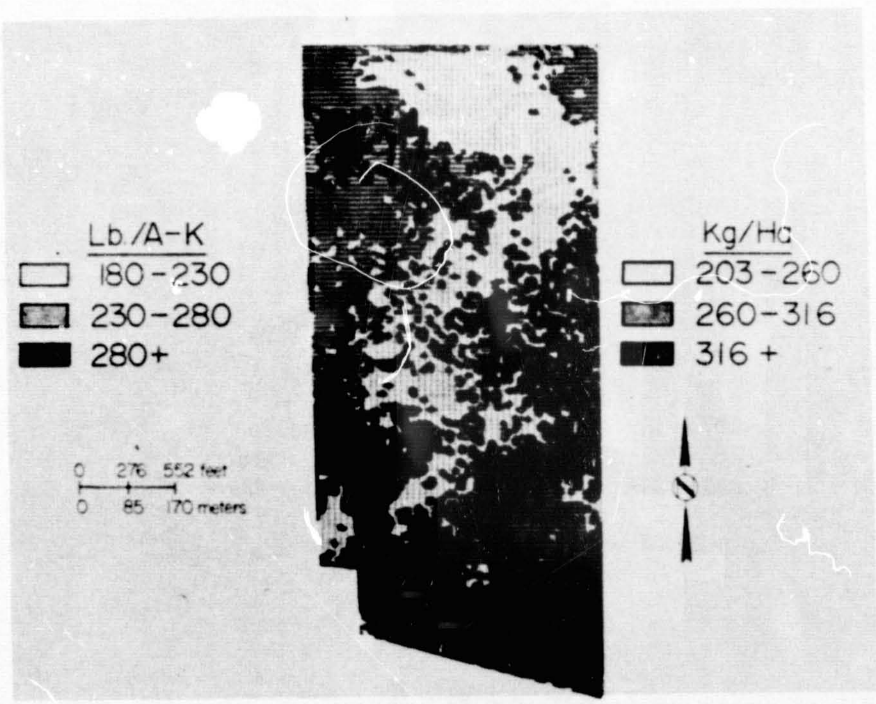


Figure 2. Organic matter content of surface soils, STA 6, July 1970

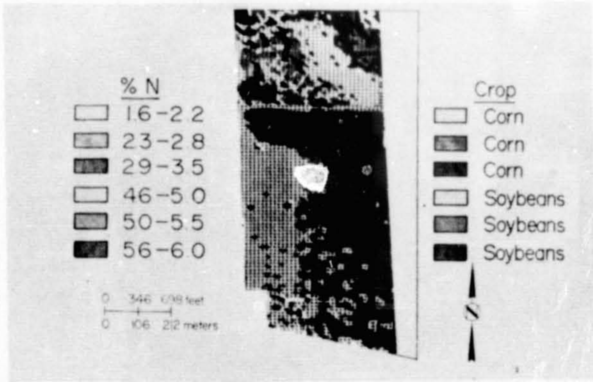


a. Extractable P

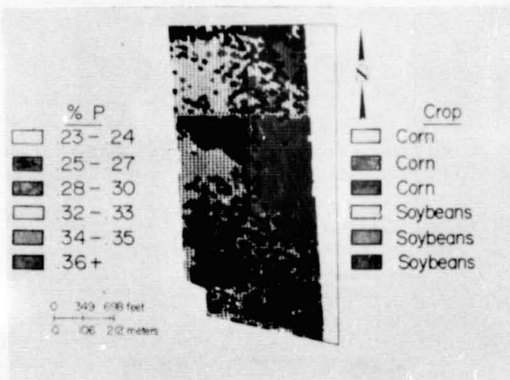


b. Exchangeable K

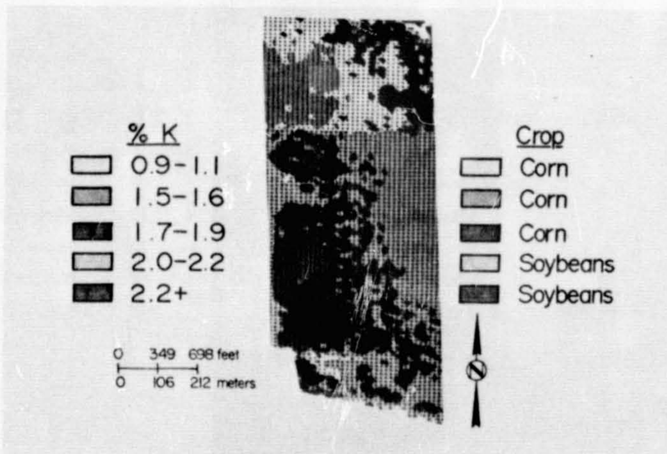
Figure 3. Computer map of extractable soil phosphorus and exchangeable soil potassium, STA 6, July, 1970



a. Plant N

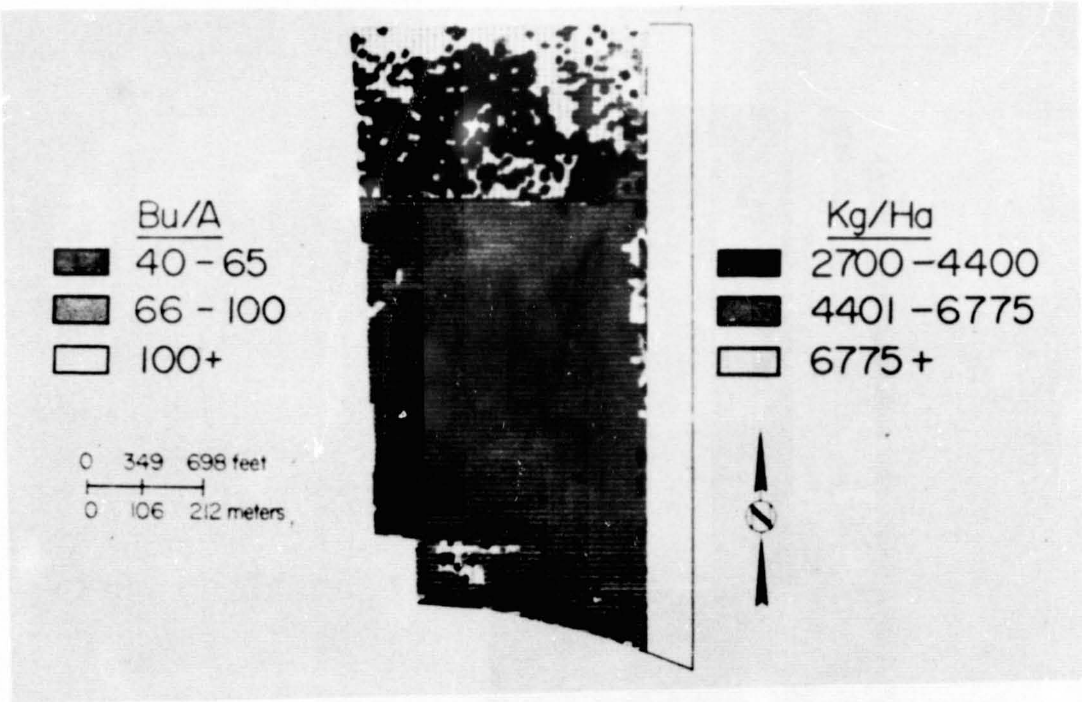


b. Plant P

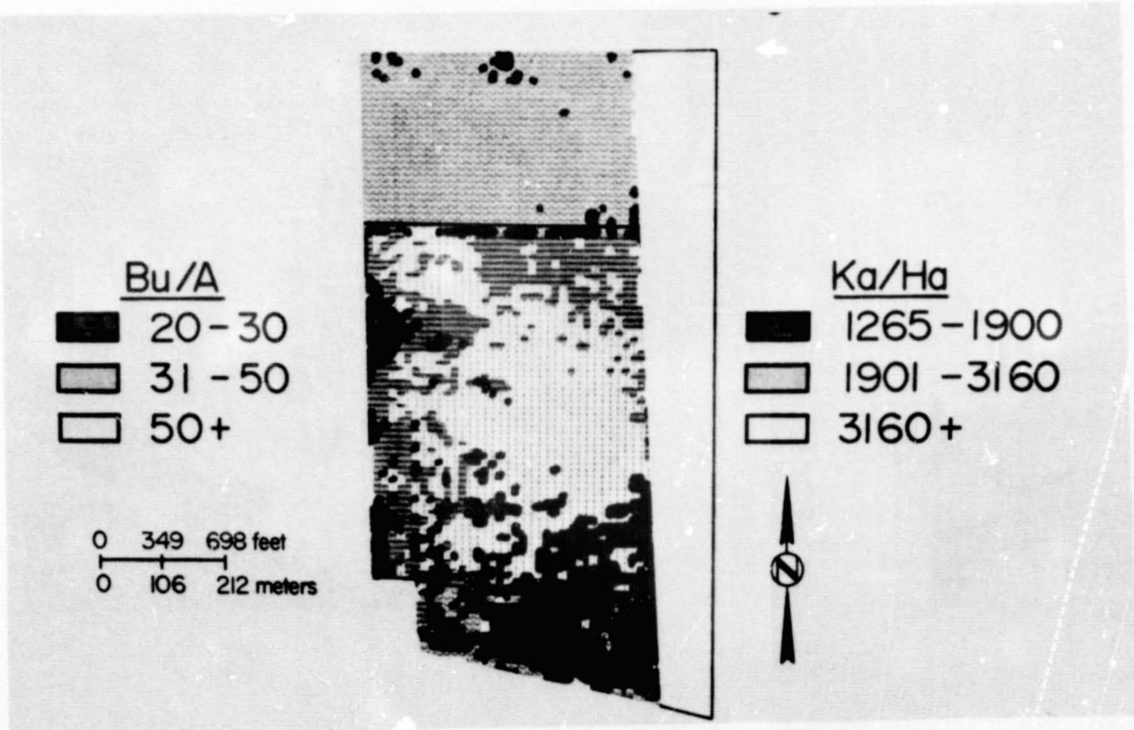


c. Plant K

Figure 4. Sepctral maps representing different levels of plant nitrogen, phosphorous, and potassium, STA 6, August 1970



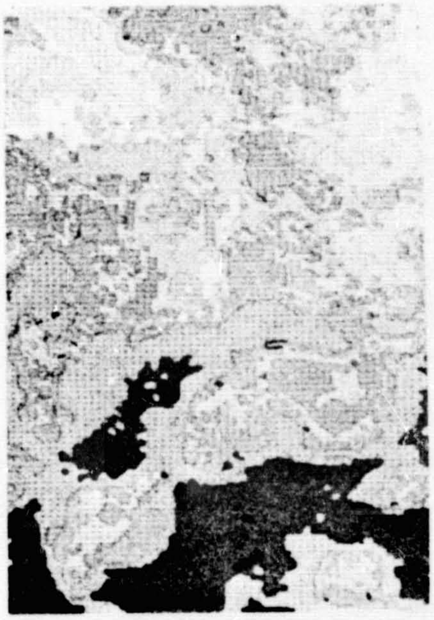
a. Corn yield
(upper one-third of field)



b. Soybean Yield
(lower two-thirds of field)

Figure 5. Computer maps relating crop yield to spectral response.
STA 6, August 1970

(a)

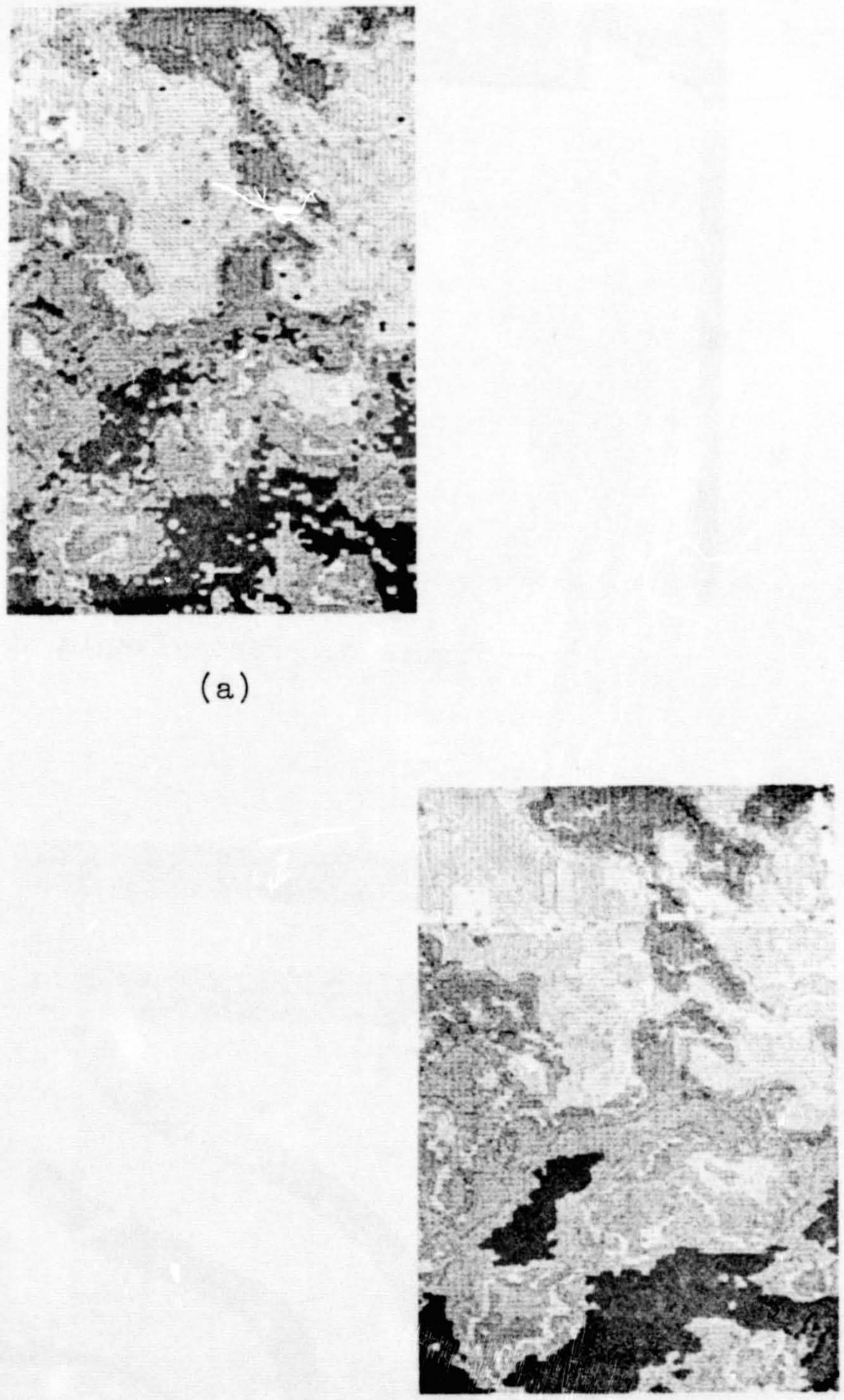


(b)

(c)

Figure 6. Fourteen spectral classes of soils in selected fields from flightline 212, Montgomery County, Indiana, 12-channel (0.4-1.8 μm) classification

Reflectance data used to select classes:
(a) Total (b) Visible (c) Infrared



(a)

(b) (c)

Figure 7. Fourteen spectral classes of soils in selected fields from flightline 212, Montgomery County, Indiana, 4-channel classification

Reflectance data used to select classes:
(a) Total (b) Visible (c) Infrared

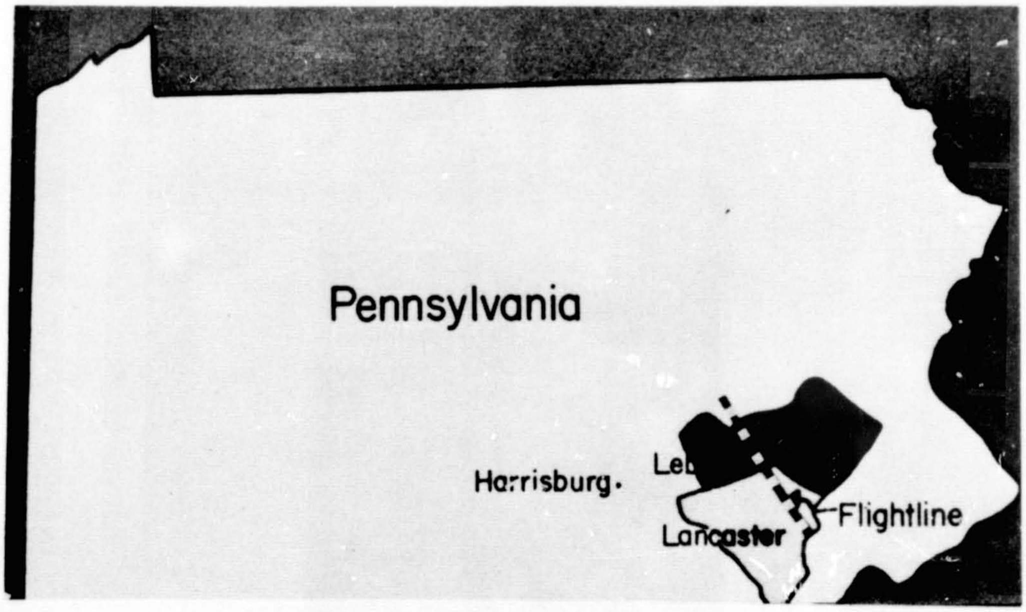


Figure 8. Pennsylvania test site

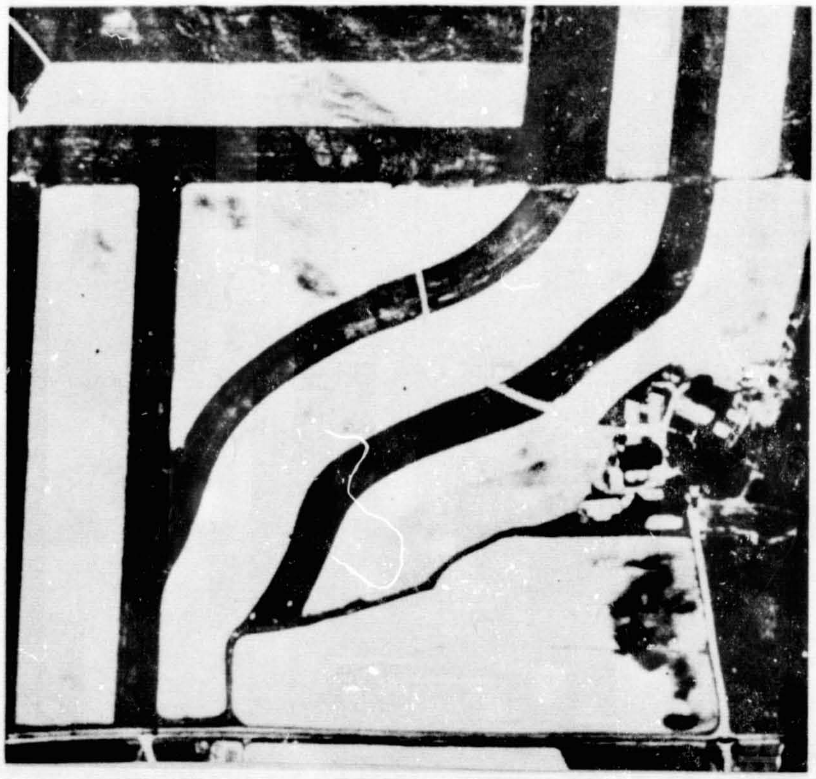
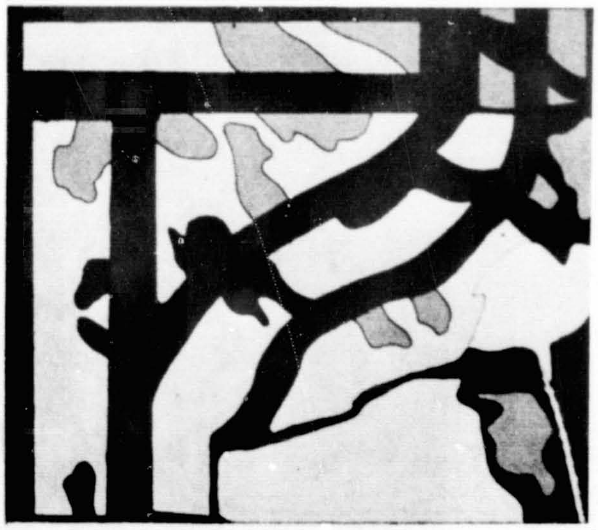
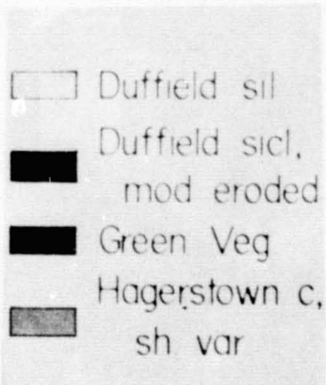


Figure 9. Aerial photograph of test field in Lancaster County, Pennsylvania

(a)



(b)



Approximate Scale

0 300 600 feet

0 91 182 meters

Figure 10. Spectral mapping of limestone soils Lancaster County, Pennsylvania

(a) Multispectral Computer Map (b) Field Survey Map

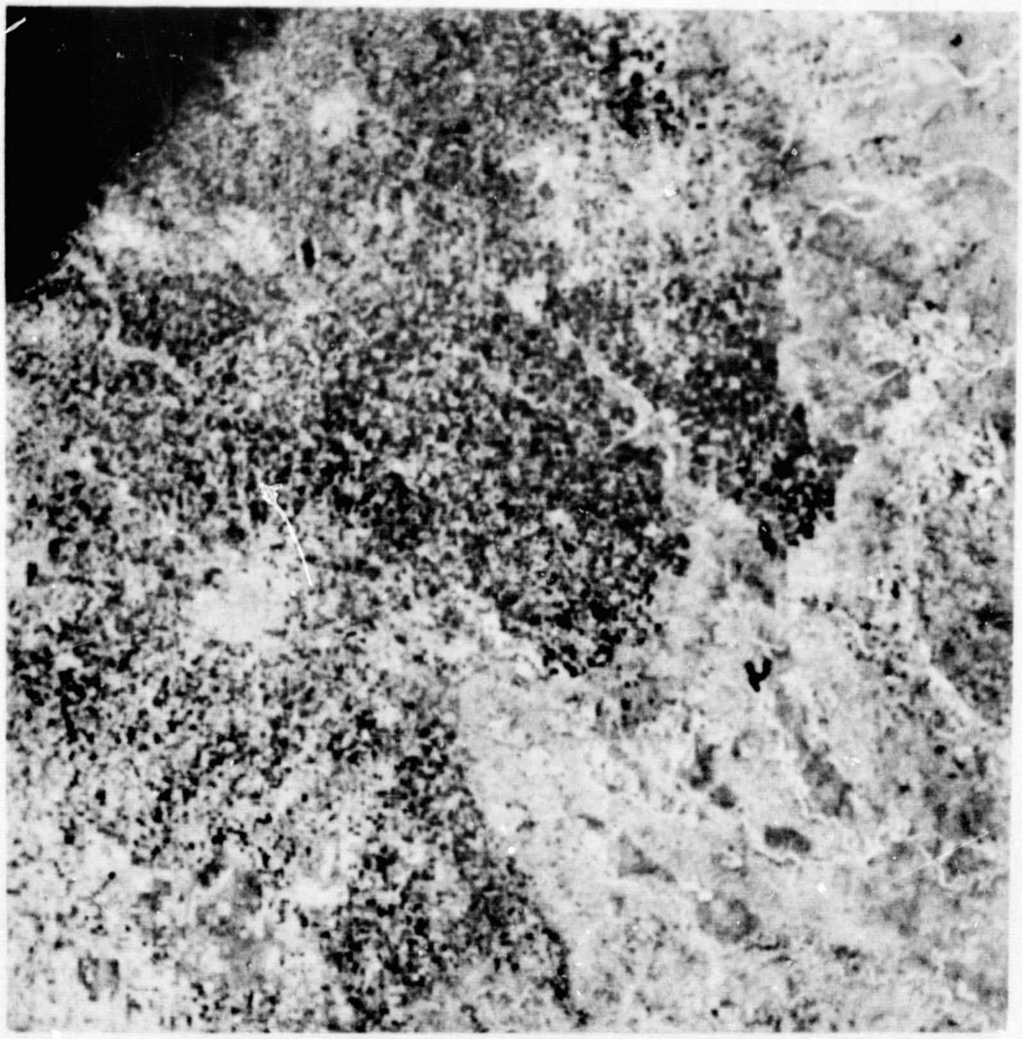


Figure 11. Apollo 9 photograph of the Lubbock, Texas, region (NASA frame 3808)

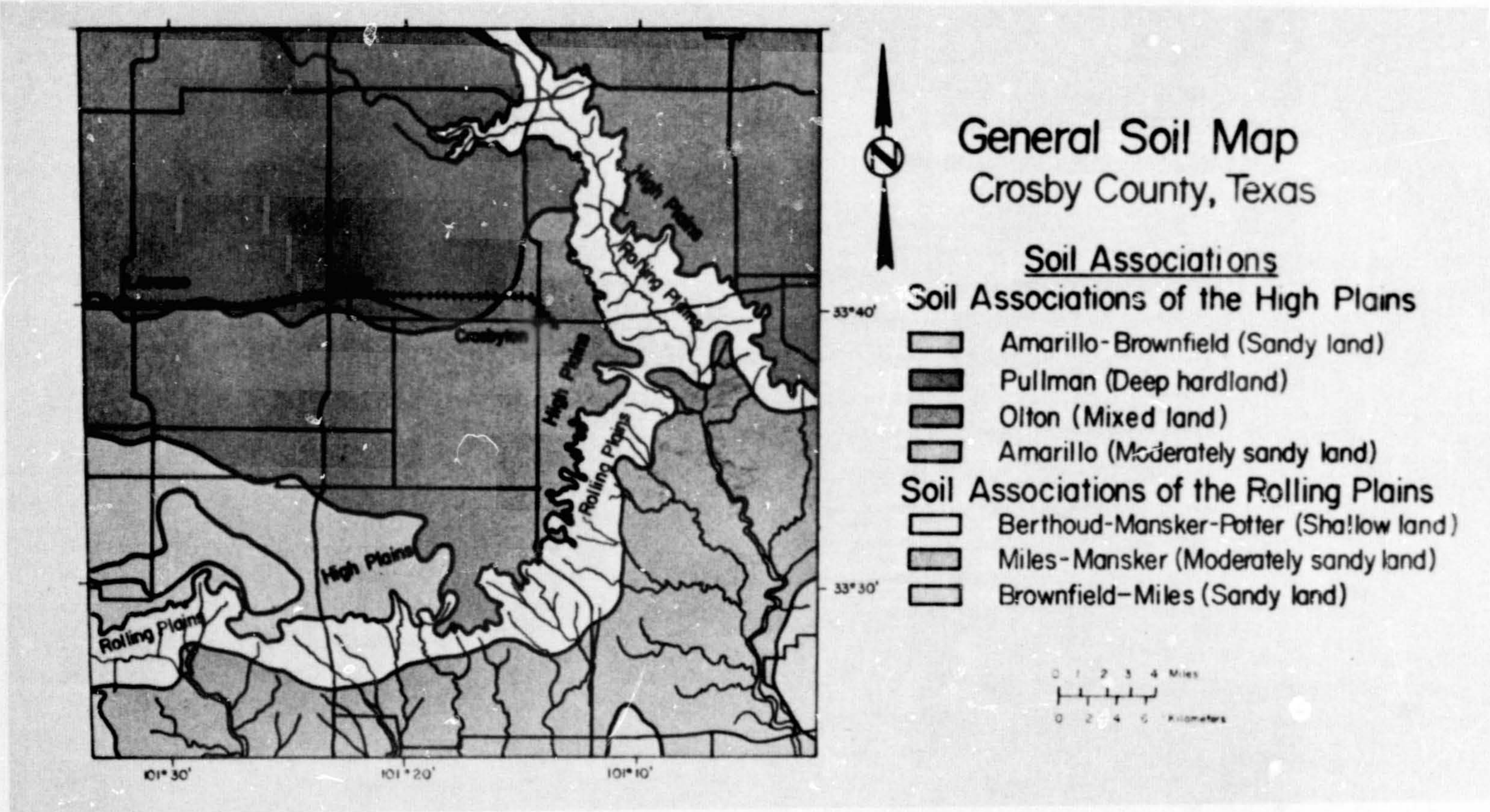


Figure 12. General soils map of Crosby County, Texas.

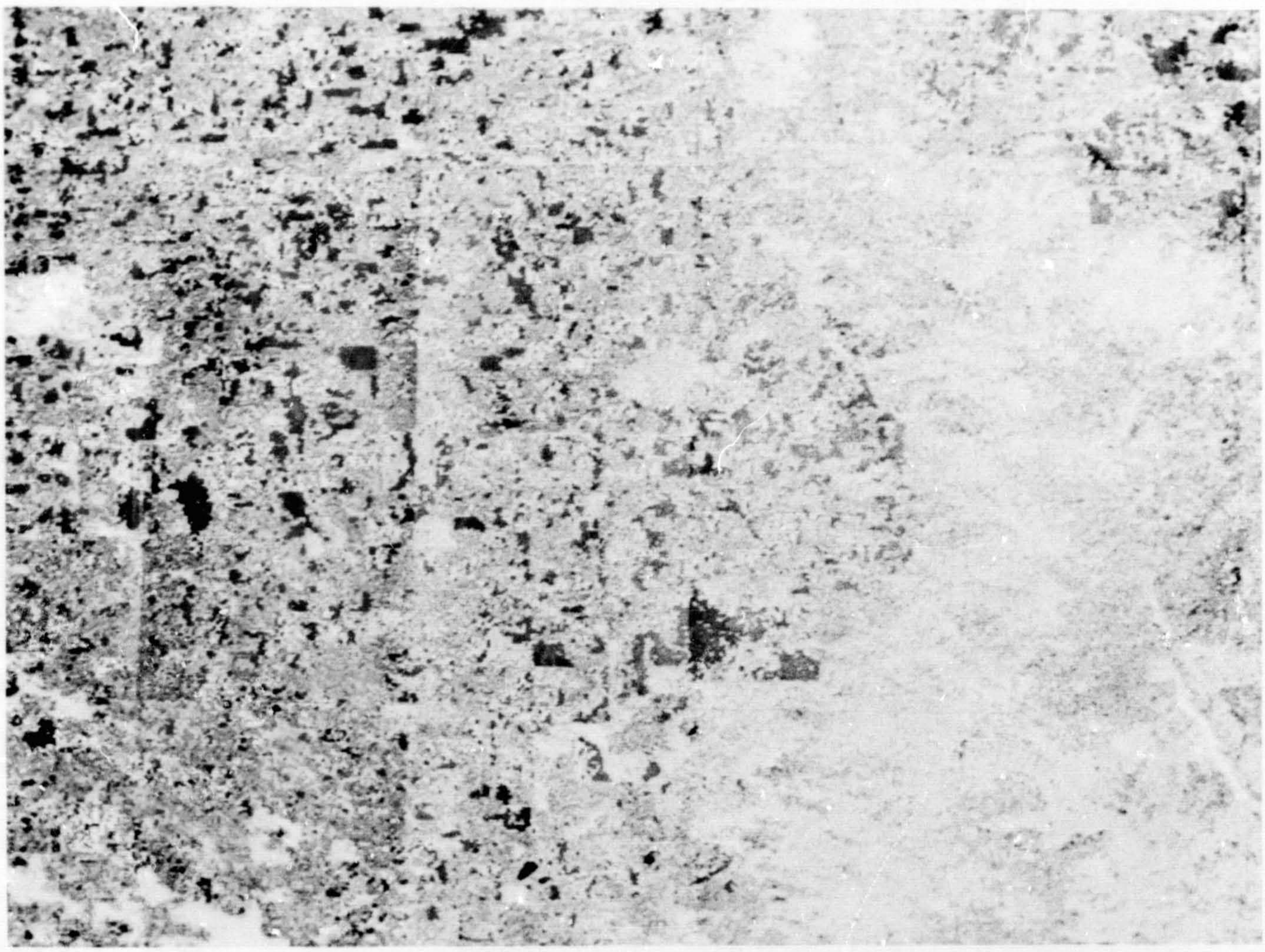


Figure 13. Spectral classification of east central portion of Crosby County, Texas; data from Apollo 9, March 12, 1969

Figure 14. Computer map of spectral classes of surface features around White River Reservior. Crosby County, Texas. Data from Apollo 9, March 1969

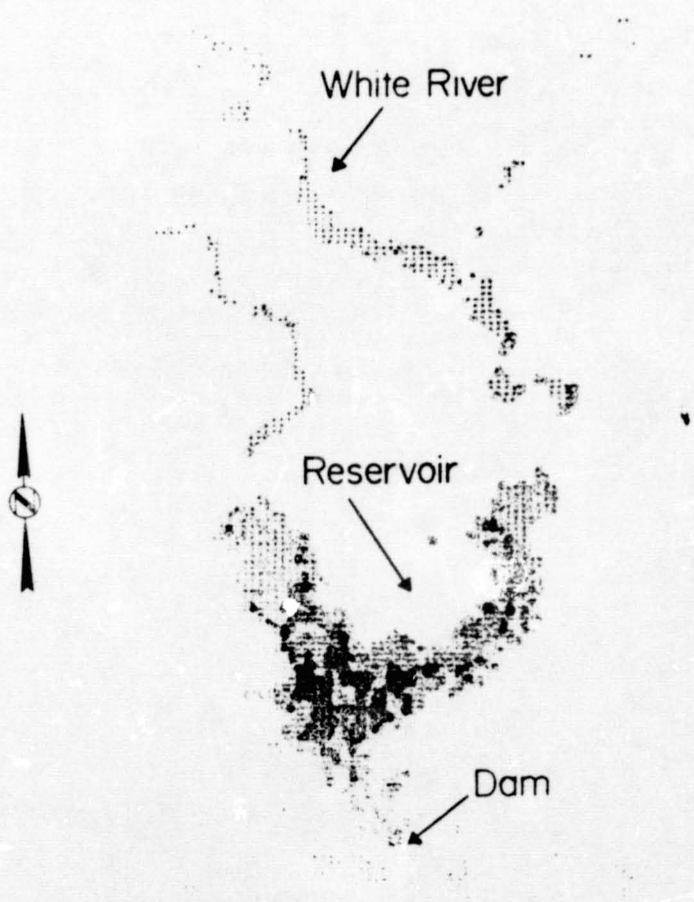


Figure 15. Computer map of the White River and Reservoir in Crosby County, Texas. Data from Apollo 9, March 1969