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Purdue University

A Look Ahead

by

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Lord Kelvin stated, "I often say that when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind; it may be the beginning of knowledge, but you have scarcely, in your thoughts, advanced to the stage of Science, whatever the matter may be."

Certainly as the world's increasing population demands more and more of the earth's resources and spews out ever increasing quantities of waste materials, the need for management of earth resources and control of the environment becomes even more mandatory. If man expects to come to understand his ecosystem, to be able to plan wise resource development programs, to effectively manage the use of resources and to maintain a quality environment; he needs to be able to observe and more importantly measure his resources and his environment. It is only then that man can hope to understand his ecosystem so he can wisely preserve and control it.

Remote sensing is the science and art of acquiring information about material objects from measurements made at a distance without coming in physical contact with the objects. All such measurements, which I will be discussing, are characteristic measurements of the electromagnetic energy radiated by such objects (Figure 1).

All materials emit electromagnetic energy for several reasons. As you are aware, physical bodies at any temperature above absolute zero (zero degrees Kelvin) radiate energy in the form of electromagnetic waves. Energy so radiated is a function of the temperature and nature of the surface of a body. The nature of radiating surfaces are described by their emissivities and are functions of the physical and chemical properties of particular materials.

The earth's surface is roughly 300° and consequently emits energy at longer wavelengths than visible red light. These waves are called infrared, meaning beyond the red. At 300°K the earth's surface radiates most of its energy at wavelengths between 2 and 15 microns. Another reason that objects radiate energy is due to the reflective properties of their surfaces. A certain portion of incident solar energy is immediately re-radiated or is said to be reflected away from objects at the earth's surface. This energy is a function of the reflectance of an object's surface and is again related to the physical and chemical properties of different materials.

Sensors which measure the energy naturally radiated by objects are referred to as passive remote sensors. Rather than rely on incident energy from the sun, active remote sensors such as radar first transmit energy to the object and measure the portion which is reflected back.

Any object or scene is made up of small radiating elements (Figure 2). The resolution of the sensor being used determines the smallest size individual radiator which can be discerned by that particular sensor. The sensor might be a human eye, camera, spectrometer, or radar.

While such sensors have radically different physical appearances, they all perform much the same function. They detect and measure characteristics of electromagnetic energy radiating from a scene. Even though sensors come in many forms, there are only four basic characteristics of this energy which can be measured. These are spatial, spectral, temporal and polarization characteristics.

Why so many instruments? Why do they look so different? The number of instruments and their differing physical appearances are indicative of the many different interactions which occur between materials and electromagnetic energy of different frequencies. For example, glass is transparent to visible frequencies and opaque to longer wavelength infrared. Sensors are designed to operate at widely differing frequencies. The kinds of measurements which can be collected in any one region of the electromagnetic spectrum are few in number.

When a sensor measures the amount of energy being radiated at an instant of time from the smallest resolved radiators as a function of their relative location in a scene, the sensor is measuring the spatial characteristics of energy radiating from a scene. When a sensor measures the amount of energy being radiated at an instant of time from the smallest resolved radiators as a function of frequency or wavelength, the sensor is measuring the spectral characteristics of energy radiating from a scene. If measurements of spectral or spatial characteristics are made at different times as a series then temporal characteristics of the radiated energy are being measured.

The relationships which exist between measurable characteristics of remotely sensed energies at different parts of the spectrum and the temperatures, emissivities and reflectances of the encountered complex radiating scenes must be understood. In addition, one needs to know the relationships which exist between the various physical and chemical properties of these complex radiating scenes and the composite effects of the temperatures, emissivities, and reflectances of their component parts.

The researcher must learn enough to develop a deterministic or statistical model relating these measurable energy characteristics to physical and chemical properties of the scenes within the geographic area of interest (Figure 3). These models must be developed before data can be collected by remote sensing.

Photographic emulsions, photomultiplier tubes and solid state detectors can all be utilized in remote sensors to directly record electromagnetic energy occurring at frequencies from ultraviolet through the visible into the reflective infrared region and out to one or two microns. Within this frequency region, photomultipliers and solid state detectors can measure amounts of energy more accurately than can film. While films are extremely sensitive and have very high resolution (many line pairs per millimeter), they are difficult to calibrate and control. Beyond one or two microns, film emulsions are not sensitive and solid state detector materials must be relied upon. Such detectors are sensitive throughout the thermal infrared interval to beyond 15 microns.

Film emulsions have historically been used in a qualitative capacity requiring complex human interpretation routines to extract their informational content. However, we expect in the future to learn how to calibrate and control these emulsions so that they can be used to provide some quantitative measure of spectral energy adequate for certain applications. Calibrated black and white panchromatic film can provide a quantitative measure of spectral energy. Color film emulsions cannot provide such measurements; they provide measures of color. Recognition of objects on a basis of color can be quite different from recognition on the basis of spectral energy characteristics. All materials which have the same color do not necessarily have the same spectral emission properties.

So far little has been discussed about the data which can be acquired in the data acquisition phase of remote sensing and how these data may be related to the properties of the scene. The next important phase of remote sensing involves the steps required to reduce these data to information. Essentially one can utilize either human analysts, machines or a combination of the two. When there are large amounts of data needed or where great precision is required the concept of machine processing is an attractive one.

At LARS we have devoted ourselves to the specific task of marrying computers, humans and measurements instruments. Computers are not smart, but they are clever tools. This electro-mechanical slave will perform yeoman service if we supply it with the proper data and proper instructions. Consider some of the advantages of a happy marriage of humans, computers and measuring instruments:

- Sensor operation can be faster and longer
- More information can be derived in a given time interval
- Comparisons of derived data with built-in reference standards, tolerances, or specifications are quicker by orders of magnitude
- Proper provisions can be made for strict control of test operations by humans
- Systematic errors due to operator bias are eliminated
- Test data can be displayed automatically in any of several forms -- paper or magnetic tape, punched cards, line printers or tele-typewriters, automatic graphic recorders or X-Y plotters and others.

These factors become more important as the complexity of measurements increase and as we need to more quickly perform and interpret measurements.

In many applications, one needs to closely examine various possible measurements in search of those which may be handled in relatively small quantities. Optical processing techniques provide a promising means for automatically processing spatial data in the future.

Alternatively, multispectral and time varying multispectral data are particularly amenable to machine processing (Figure 4).

Such data, therefore, are extremely attractive as are the remote sensors which can collect them (Figure 5). Computers can be programmed to recognize "patterns" within these data which are indicative of scene properties of interest. However, in this approach a human must properly program a computer to use pattern recognition techniques.

At LARS/Purdue, in our research, we are trying to learn the kinds of measurements required in various applications and how to best teach the computer to recognize meaningful patterns from these data (Figure 6). In order to teach the machine significant patterns, we have selected a relatively small amount of data from known areas which are representative of the different existing scenes of the region. These are referred to as training samples. The vast majority of data can then be processed automatically.

How does one go about applying all of this to an application of interest? In our soils applications research, we have been interested in examining the possible correlation that might exist between different properties of soil types and the spectral characteristics of their emitted and reflected radiation. In particular, we set out to study the effects of soil organic matter content on the spectral properties of soils. A 60 acre field was selected as the primary research area. Multispectral measurements were collected from an aircraft during a noon period in May of 1969 (Figures 7, 8). At the time of the flight, the area had been prepared for seeding to corn and soybeans and so was void of surface cover. The surface soil patterns were typical of the gray brown podzals formed under forest vegetation. One hundred ninety seven one-kilogram surface soil samples (Figure 9) were obtained and taken to the laboratory to be analyzed for organic matter content by the Walkley and Black method. A soil map of the region (Figure 10) was also prepared as a part of the ground truth. The soil categories in the study area are given in Table 1.

Table 1. Seven soil categories in study area, Dieterle Farm

Del Ray Silt Loam
Fincastle Silt Loam
Kokomo Silty Clay Loam
Metea Sandy Loam
Russell Silt Loam
Toronto Silt Loam
Xenia Silt Loam

The resolution of the airborne spectrometer is such that measurements were made of each 100 square foot area. Energy measurements were made in 12 frequency bands. Five levels of organic matter content based on the results of the laboratory analysis and other factors are given in Table 2. In total, 197 airborne measurements were selected from the areas of the soil samples and were used to train the computer to recognize these five levels. The number of training samples in each category are given in Table 2.

Table 2. Five categories by percent organic matter and number of samples used in training.

% Organic Matter	Number of Samples
0 - 1.5	46
1.5 - 2.0	63
2.0 - 2.0	18
2.5 - 3.5	37
above 3.5	33

After the computer was trained, it was instructed to classify all of the data collected over the area on the basis of its training and to printout the results (Figure 12). The particular spectral wavelengths chosen for the training analysis were:

0.46 - 0.48 microns

0.62 - 0.66 microns

0.80 - 1.00 microns

1.50 - 1.80 microns

Also, a soil mosaic was constructed from portions of each of the 197 surface soil samples to provide a model of the surface soil patterns (Figure 11).

It was observed that with refinement of the organic matter classes areas of severe to moderately severe erosion could be automatically identified. As a part of the analysis, the average radiance level of each training sample was plotted against soil organic matter content for each of the 12 frequency bands (Figure 13). Linear regression analysis gave an r value of -0.74. It can be noted that the plotted data seems to indicate that a linear relationship may not be valid over the entire range of organic matter content. However, it appears that above 2.0 or 2.5 percent organic content, there may be a linear correlation with a much higher value.

The same training sets were then used to automatically classify all the points in an area 24 miles long and one mile wide. The results look very promising (Figure 14).

The results of this research are fast establishing the feasibility of using remote sensing and automatic processing to prepare maps by organic matter for large areas.

Generally, at LARS we have teams of scientists investigating applicatioas of this remote sensing technology to situations involving the following natural materials

- vegetation
- soils and geological formations
- water

The follwoing is a description of some of our work and results at LARS. Initially, our investigations were directed toward the automatic identification of gross earth surface cover types (Figure 15). We have been able to map green vegetation, soil and surface water from data collected over central Indiana (Figure 16). Surface water has been identified with high reliability, even when it is not visible to the eye, and the areas covered by water are scarcely if at all discernable (Figure 17). However, combinations of spectral measurements beyond visible red permitted complete and automatic identification of all inundated areas. We are currently investigating the possibilities of sensing water quality. To date, spectral measurements have permitted the sorting of water in the White River outside of Indianapolis into a number of categories (Figure 18).

Since these data were collected for other purposes, no water samples to detect the content of the categories were collected at the time of flight. However, we hope in the future to be able to relate spectral categories to different chemical and organic properties of such water resources.

Some of our efforts are now being directed towards the uses of these techniques to measure the thermal characteristics of bodies of water. The monitoring of these thermal characteristics is becoming increasingly important as the use of water resources becomes more intense.

As previously mentioned, our soils scientists are interested in the use of this technology to automatically map organic matter content.

Additionally, we have been successful to date in our attempts to quantify and map soil color measurements which as you know, can be related to other soil properties. The color patterns of the soils of the study area are shown in Figure 19, ranging from light to dark and including reddish yellow tones of subsoils in eroded areas. A computer derived map of the green vegetation, soil and surface water is shown in Figure 20. The computer was trained to map the soils into two categories, light and dark (Figure 21). Next the area was mapped in three categories of soil (Figure 22), and finally in six categories (Figure 23). In this work, training samples were selected on the basis of Munsell color notations of soil samples of the area and with spectral training samples selected on the basis of color photographs of the area.

We have concluded that just as theory predicts, one can produce a more refined map of the color characteristics of an area with fine quantitative spectral measurements than can normally be produced with photography.

Much of our total research has been directed towards developing a capability to automatically recognize vegetative species and important physiognomic characteristics of species. Our flight lines over Tippecanoe County enables us to collect data over 150 square miles of the 501 square mile area in the county (Figure 24).

While we have been interested primarily in automatically recognizing the major crops at critical stages of their growth--corn, soybeans, winter wheat--we have attempted to classify up to nine species. Figure 25 shows a photograph of a portion of a flight line in Tippecanoe. Computer printouts of the results of classifications of nine cover types are shown. The computer was also instructed to print only wheat, only bare soil and water, and only red clover. Figure 26 summarizes the recognition accuracies of this particular classification analysis.

We have also classified crops into categories such as row crops and cereal grains (Figure 27). Often this simpler recognition task can be accomplished with extremely high accuracy.

This last spring, the system was trained to recognize the spectral patterns of deciduous trees and programmed to analyze data from a selected area. In the computer printout in Figure

28 the results are shown and are encouraging. Similarly, we have been able to map trees in orchards in Texas and elsewhere in the U. S. Mr. Joe Bell of your organization will go into more detail in applications of direct interest to your work which he has researched. As many of you may know, we had the pleasure of having Mr. Bell on our staff for a year.

Boresited cameras with different filters and proper controls can produce some quantitative measures of spectral energy adequate for certain applications. Apollo 9 carried four such boresited cameras. One was loaded with color infrared film and the other three with black and white film. Each camera had a different filter. This particular system was not calibrated in any way. I, therefore, consider these to be poor spectral measurements. However, NASA and USDA requested that we apply our LARS technology to these data.

The area of study is approximately 110 miles square. A microdensitometer was used to scan the photograph and digitize 1000 points per inch (20 line pairs per millimeter). These data were stored on magnetic tape. The computer was programmed to printout an alpha numeric gray scale presentation utilizing only every 6th point (4 line pairs/mm) (Figure 29). The important notion here is that every digitized point was in machine language and could be manipulated at will--accurately and rapidly. The magnitude of data in such a complex scene was very great.

The three different black and white frames at 0.47-0.61 microns, 0.59-0.71 microns and 0.68-0.89 microns (visible and reflective IR) were similarly digitized and stored on magnetic tape. Since boresiting was not exact, the data was spatially registered electronically and fed to the computer.

A computer gray scale printout of the area at a full resolution of 20 line pairs per millimeter is shown within the black lines in Figure 30. NASA had collected considerable ground truth within an area marked by the dotted lines. Figure 31 is a gray scale printout at a full 20 line pairs per millimeter. The data were automatically classified into categories of green vegetation, bare soil, salt flats or surface water (Figure 32). Training samples were selected from the data on the basis of limited ground truth collected by NASA, and accuracies were evaluated from the results within "test areas". Again ground truth of the "test areas" made the accuracy evaluations possible. The results of this were quite amazing to us. All categories were classified better than 90 per cent in the test areas.

In this fashion within hours a combination of man and machine can process data of an area some 10,000 square miles in size.

In conclusion, the success of this technique in applications is dependent on a successful blending ofproper measurement devices, machine data processors, and informed humans. By an informed human I mean, one who has come to understand the relationships between the radiation characteristics of natural materials and their material properties. While the feasibility of these techniques have been established, there is an enormous amount of effort required to develop them to the point where we will

will realize the benefits they now promise. While I have little doubt that in the future these techniques will become an important tool, I have even less doubt that much effort by people such as yourselves, the guy with the problem is required to develop this to a point where it is an effective tool.

Figure 29. A 10 level computer printout of the Salton Sea area.

Figure 30. A smaller area from Figure 29 in a 1000 points per inch gray scale printout.

Figure 31. A gray scale printout of 1000 points per inch of Dogwood area.

Figure 32. A classification of the Dogwood area into green vegetation (G), bare soil (-), saline soil (I) and water (W).

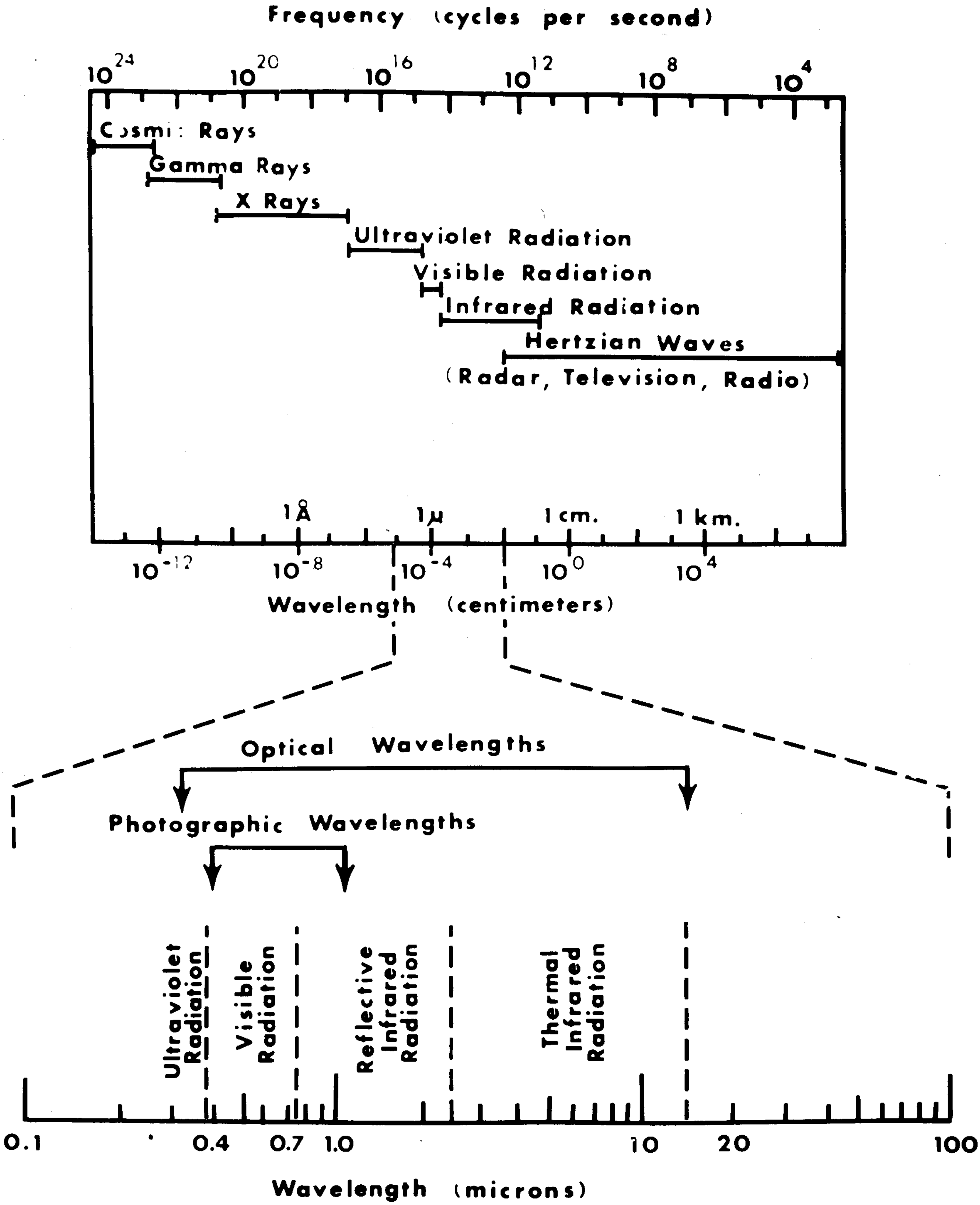

Figure 1. Electromagnetic spectrum.

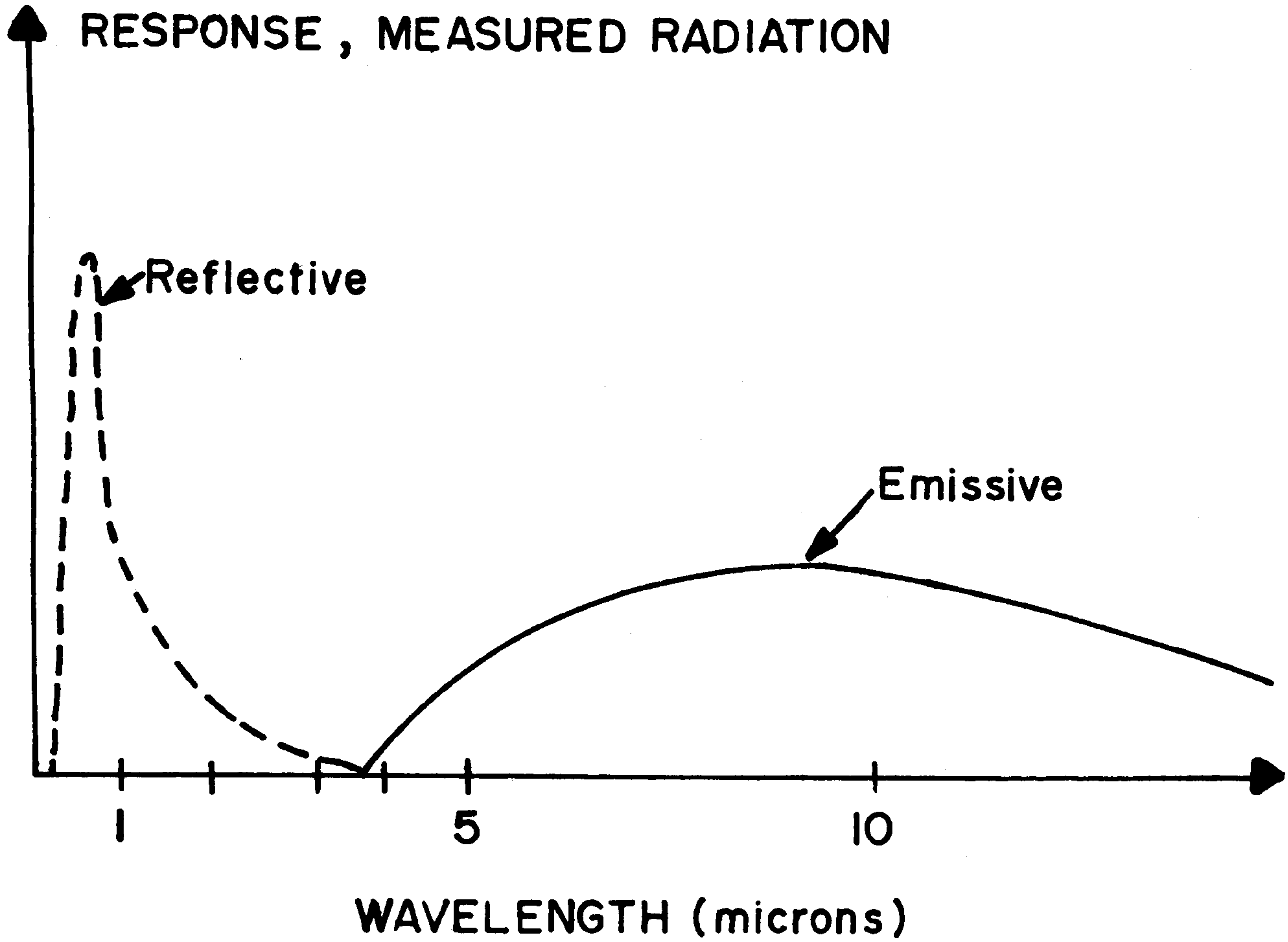

Figure 2. Frequencies where most naturally occurring energy is radiated.

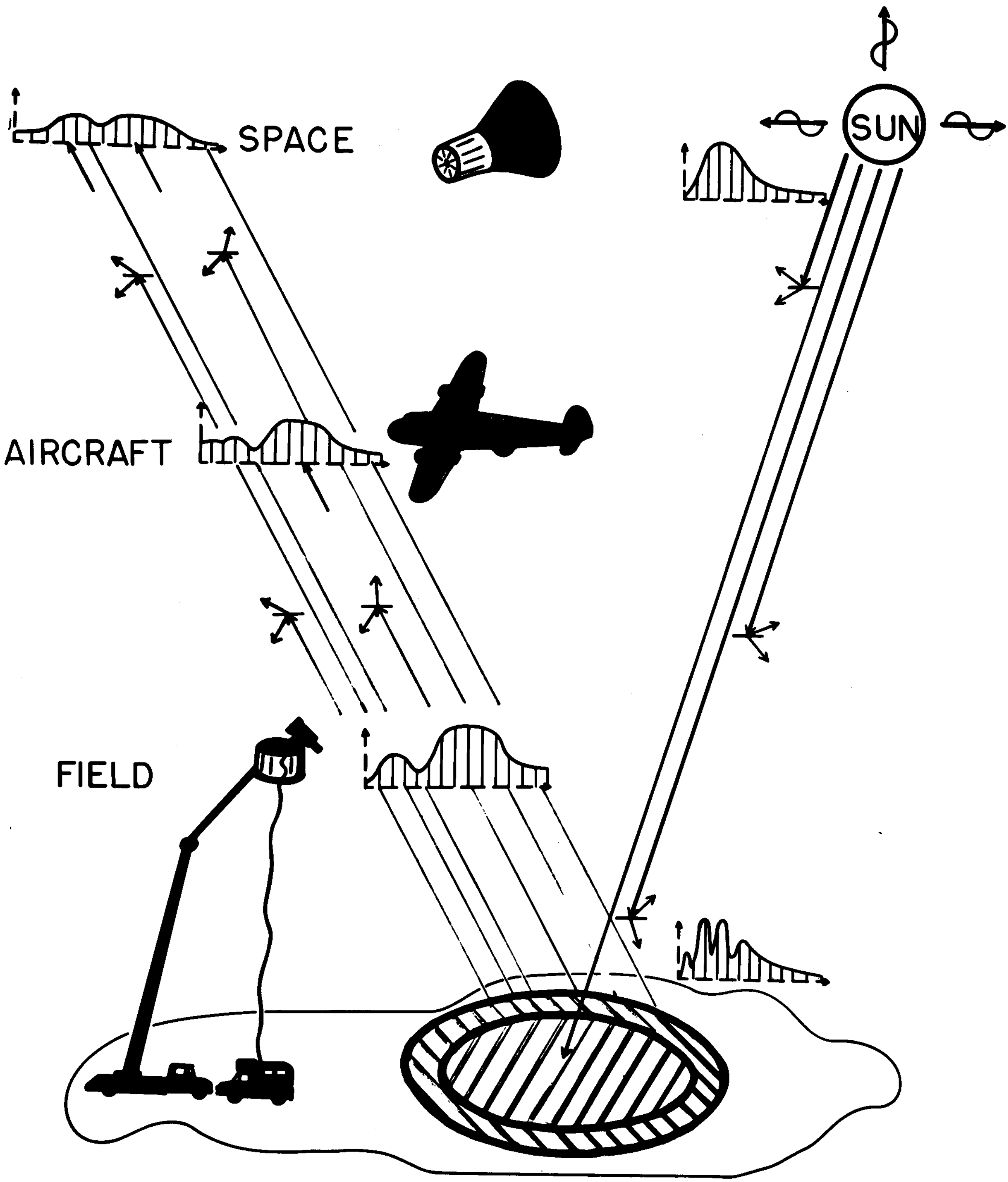

Figure 3. Remote sensing data can be acquired at different altitudes.

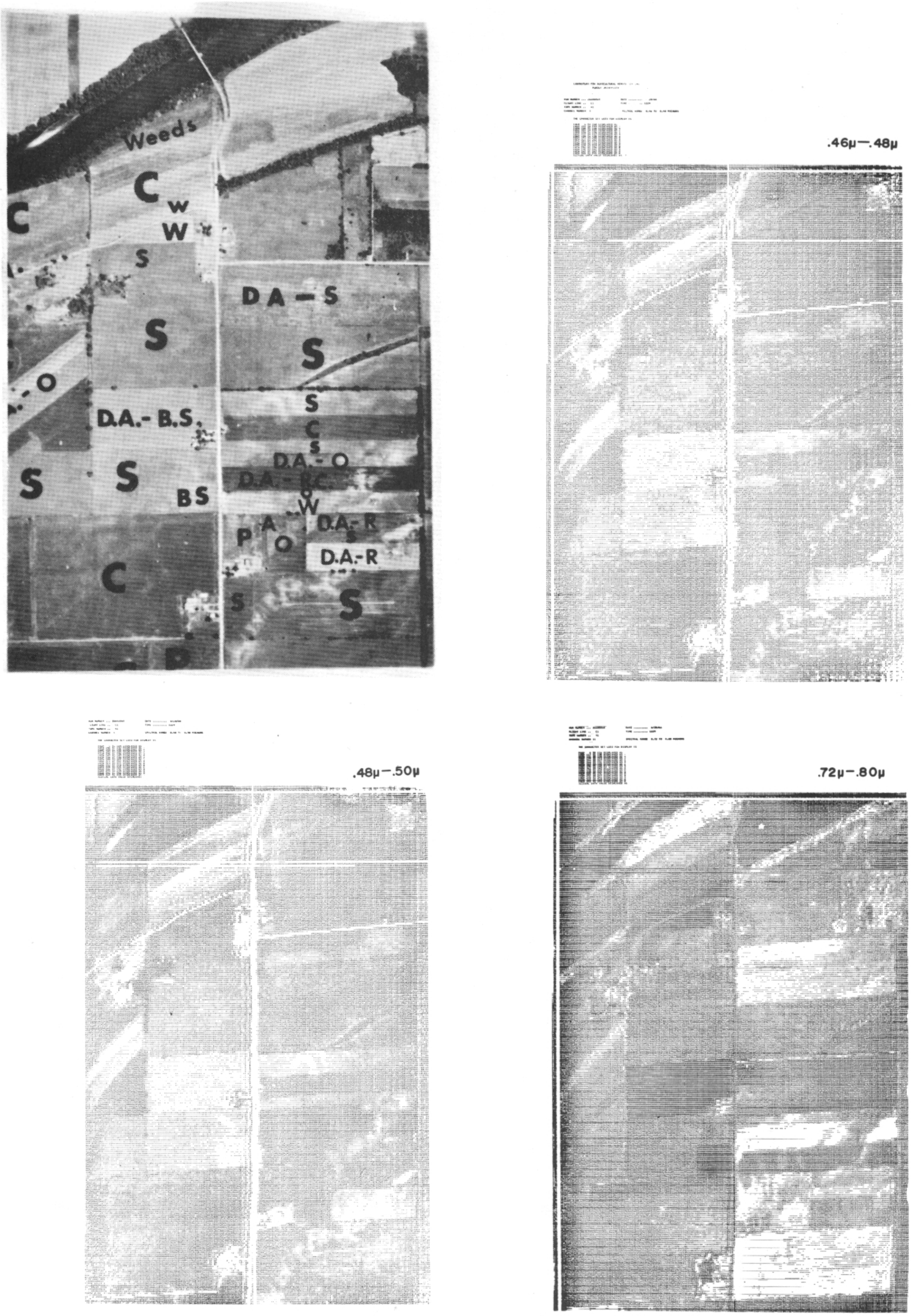

Figure 4. Images at different frequencies.

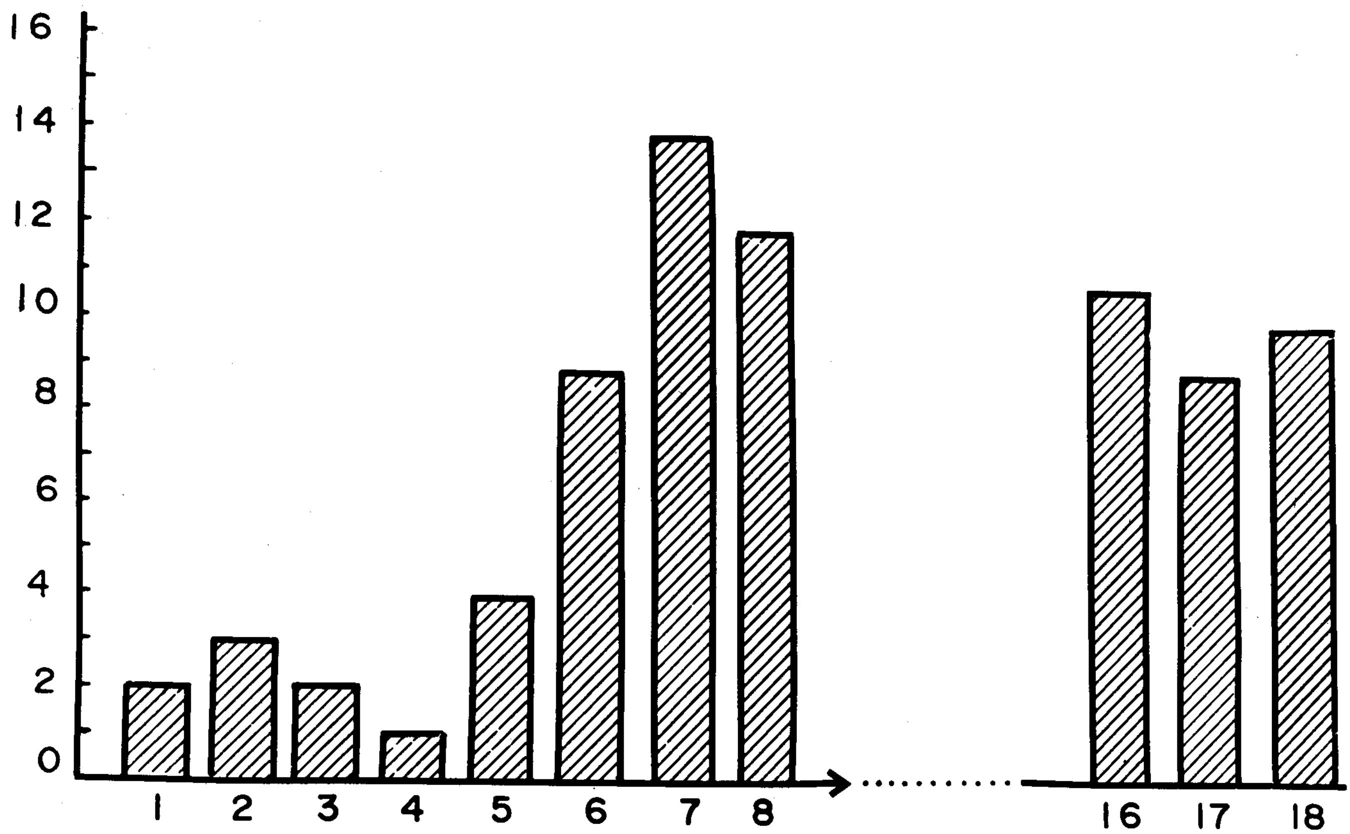

Figure 5. Theoretical multispectral radiation pattern.

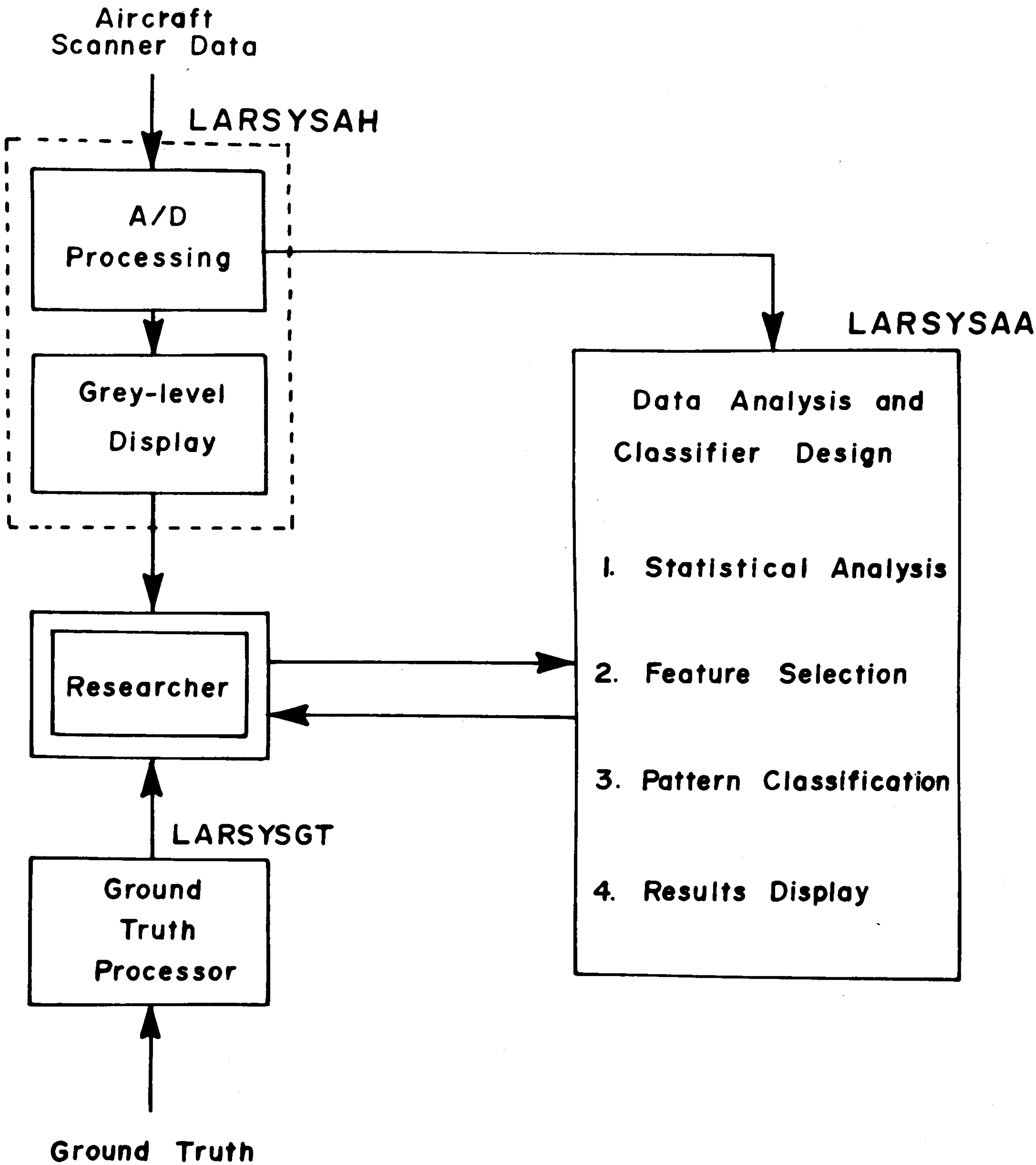

Figure 6. Outline of LARS data handling and analysis process.

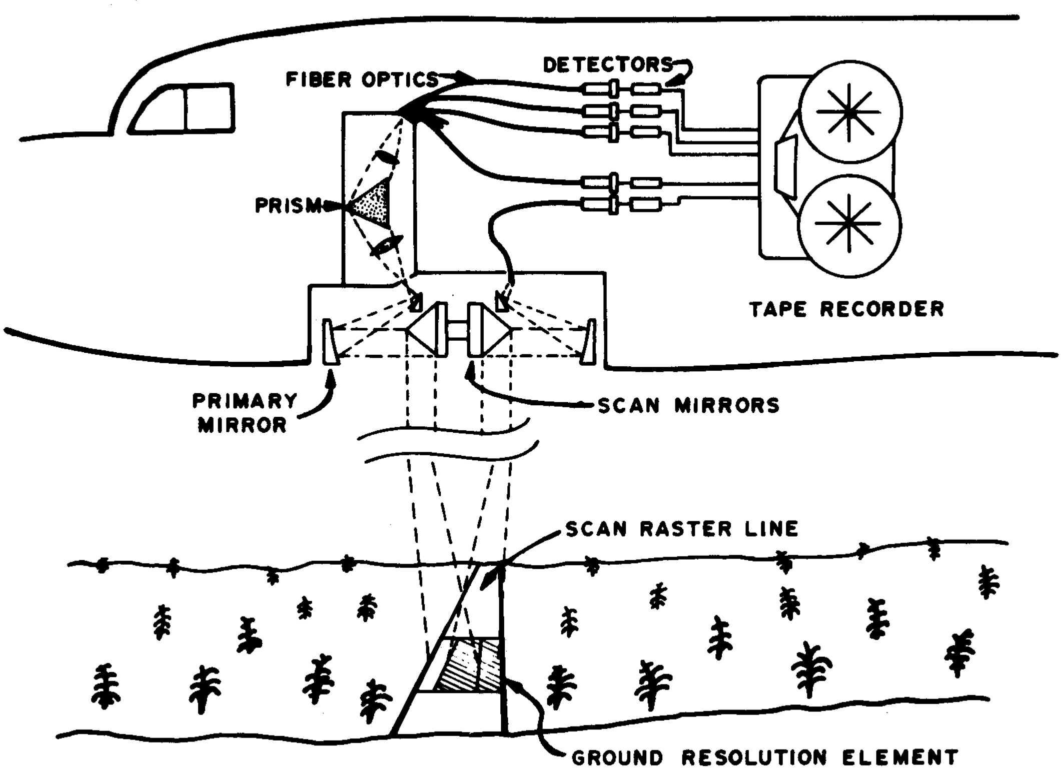

Figure 7. Illustration of data collection instruments utilized in remote sensing.

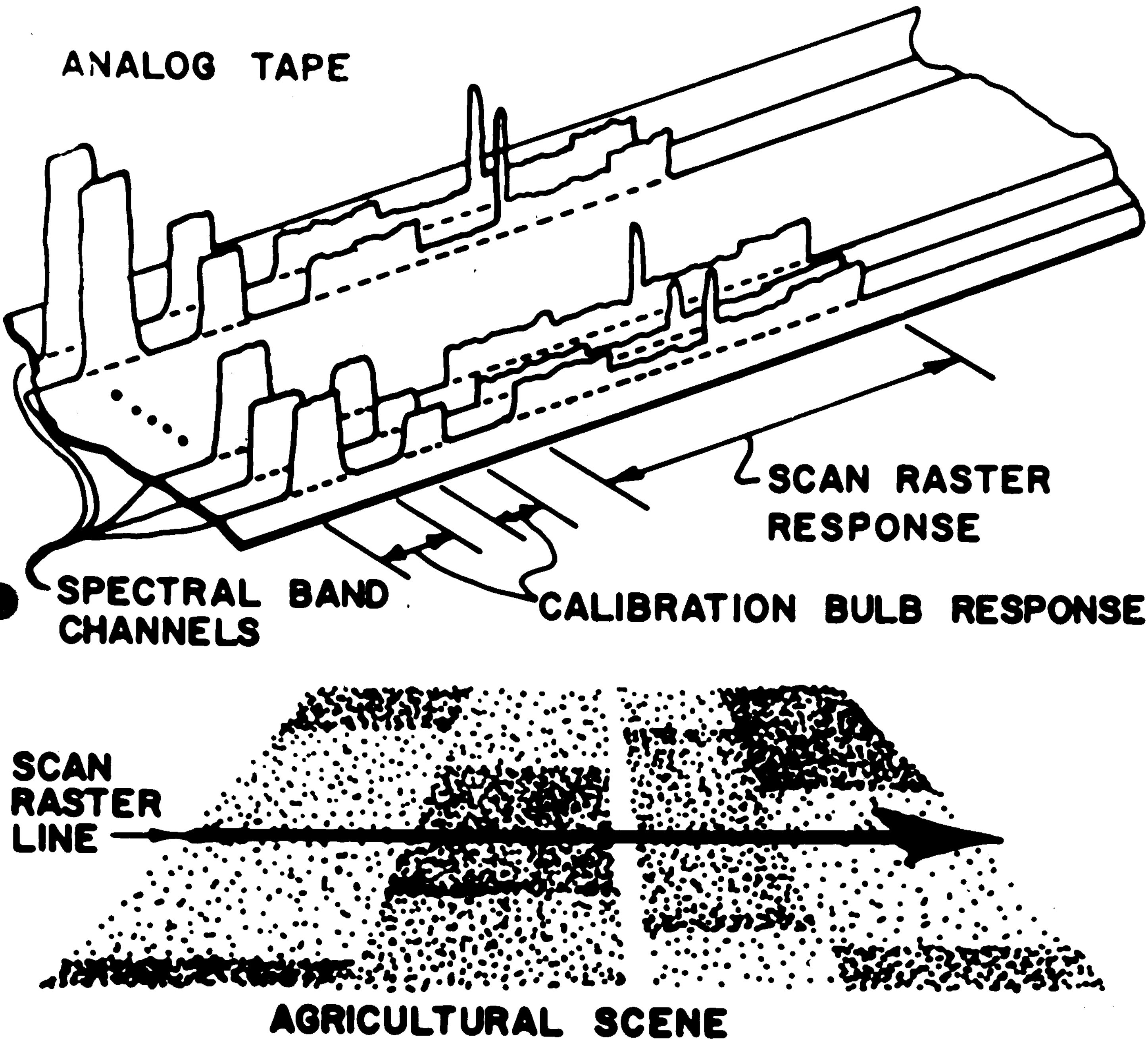

Figure 8. Illustration of analog tape recorder used to record the collected data.

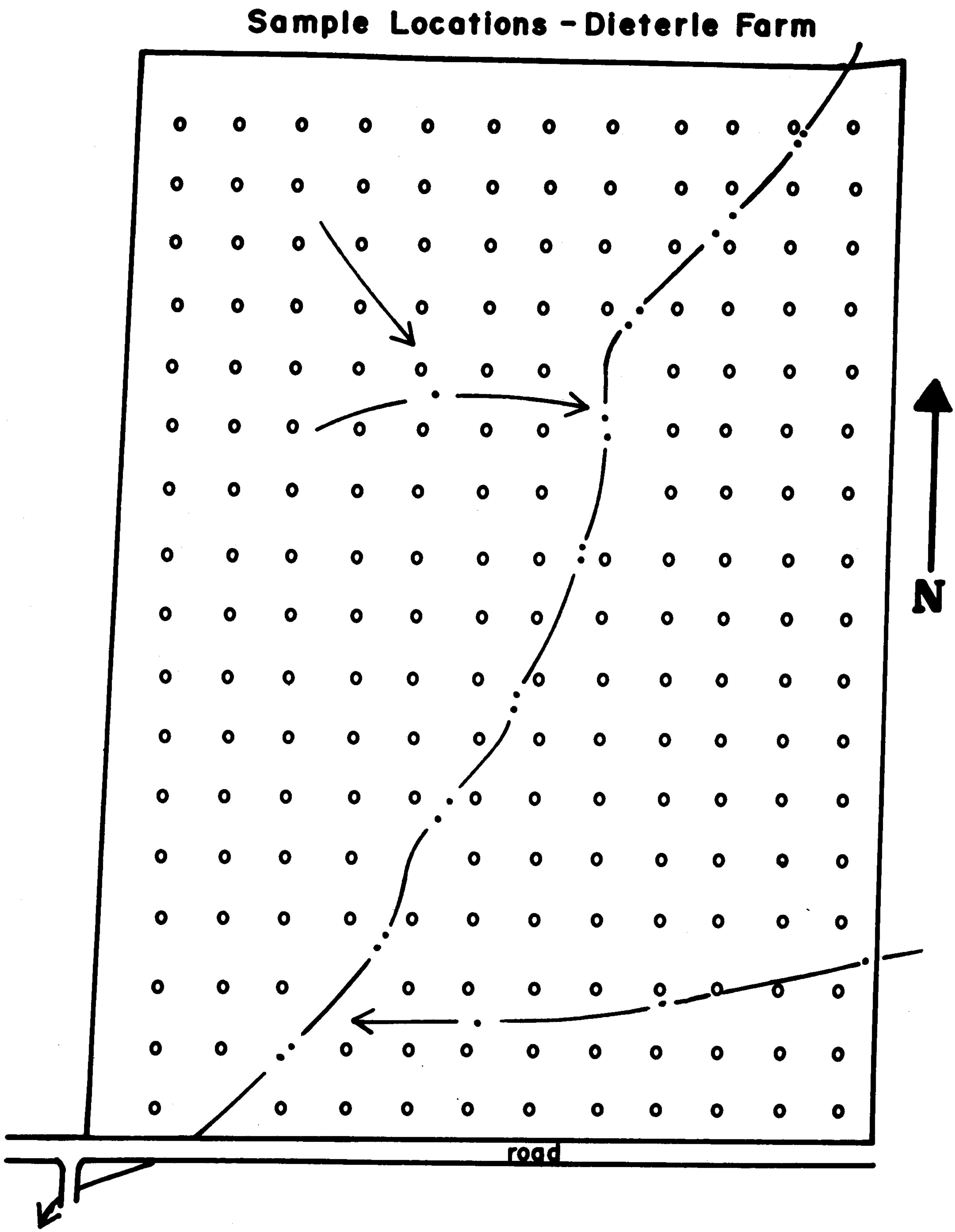

Figure 9. Location of the 197 samples which were collected.

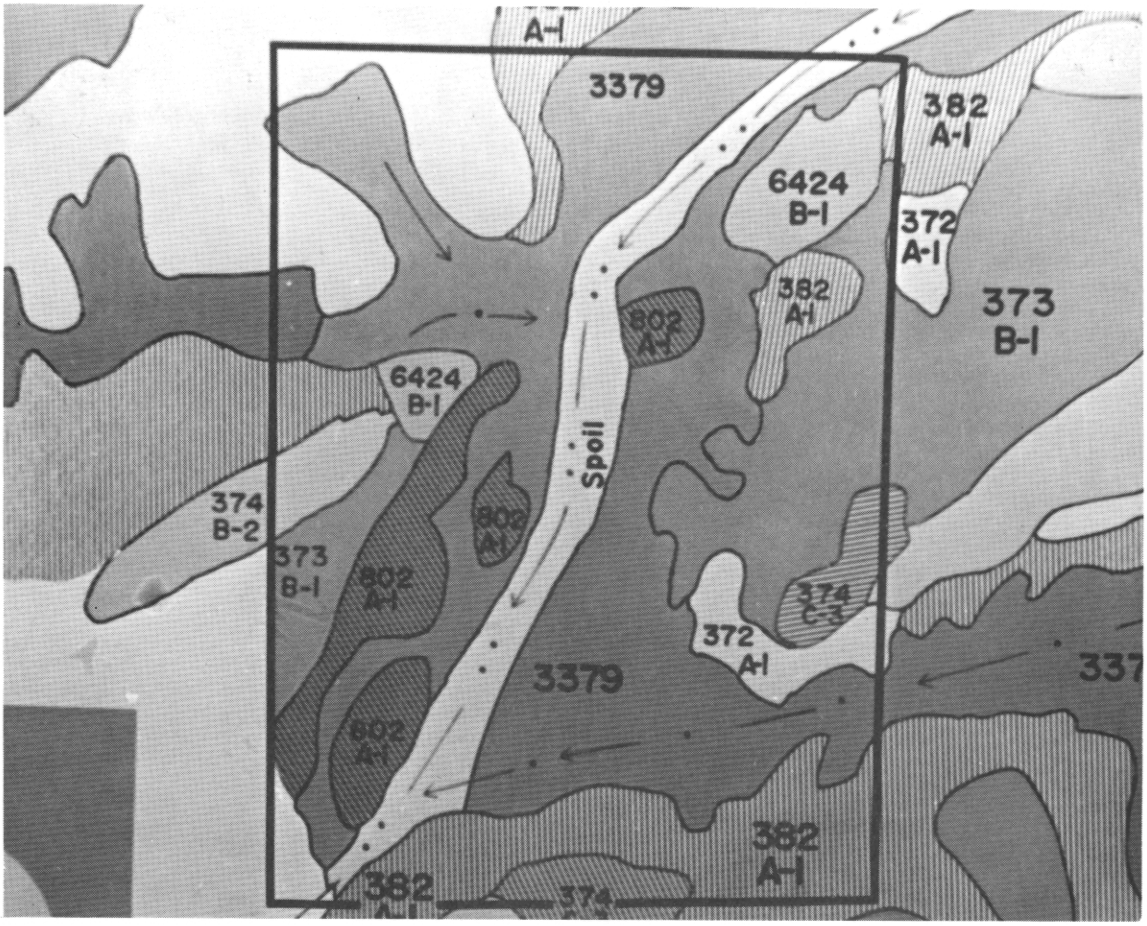

Figure 10. Soil map of the area where research was conducted. The outlined section is the same area as shown in Figure 9.

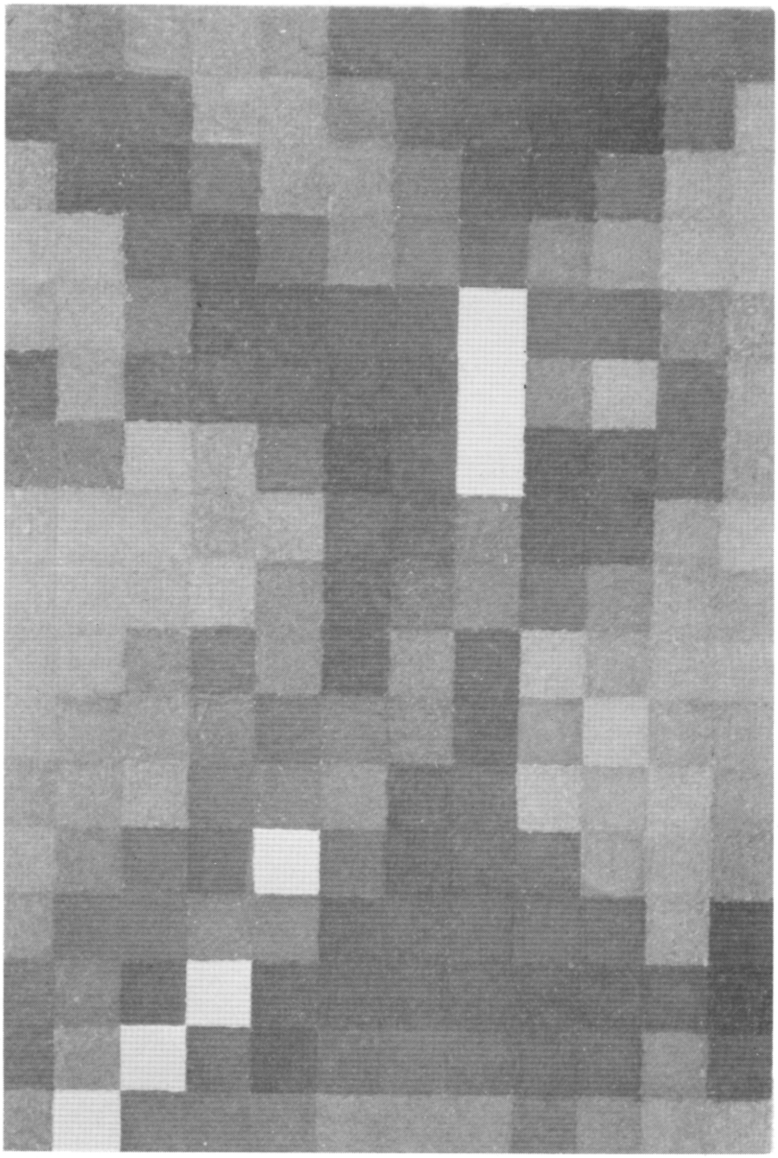

Figure 11. Mosaic of soil patterns in study area, Dieterle Farm.

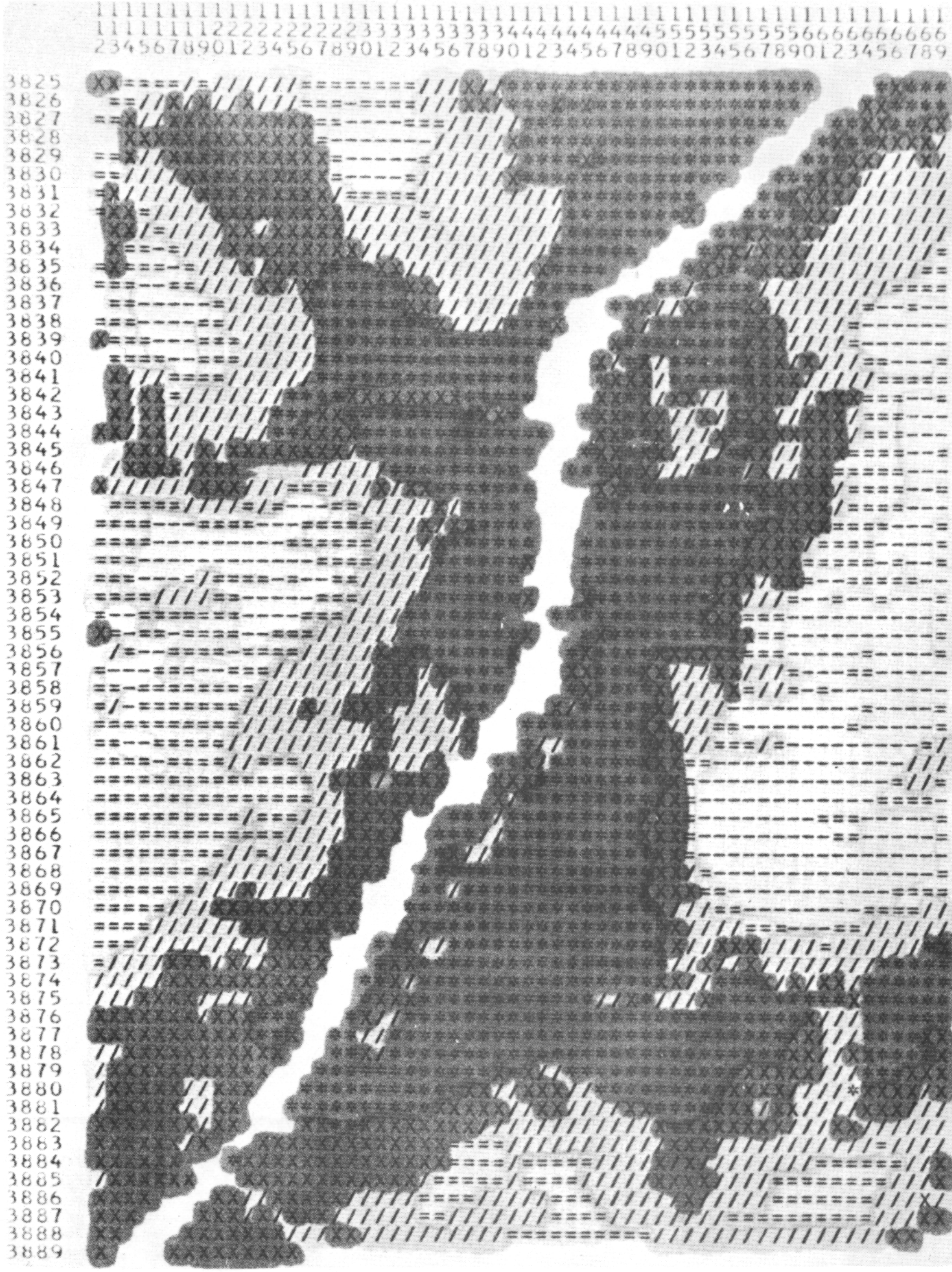

Figure 12. Computer map by organic content of the soil which was shaded manually.

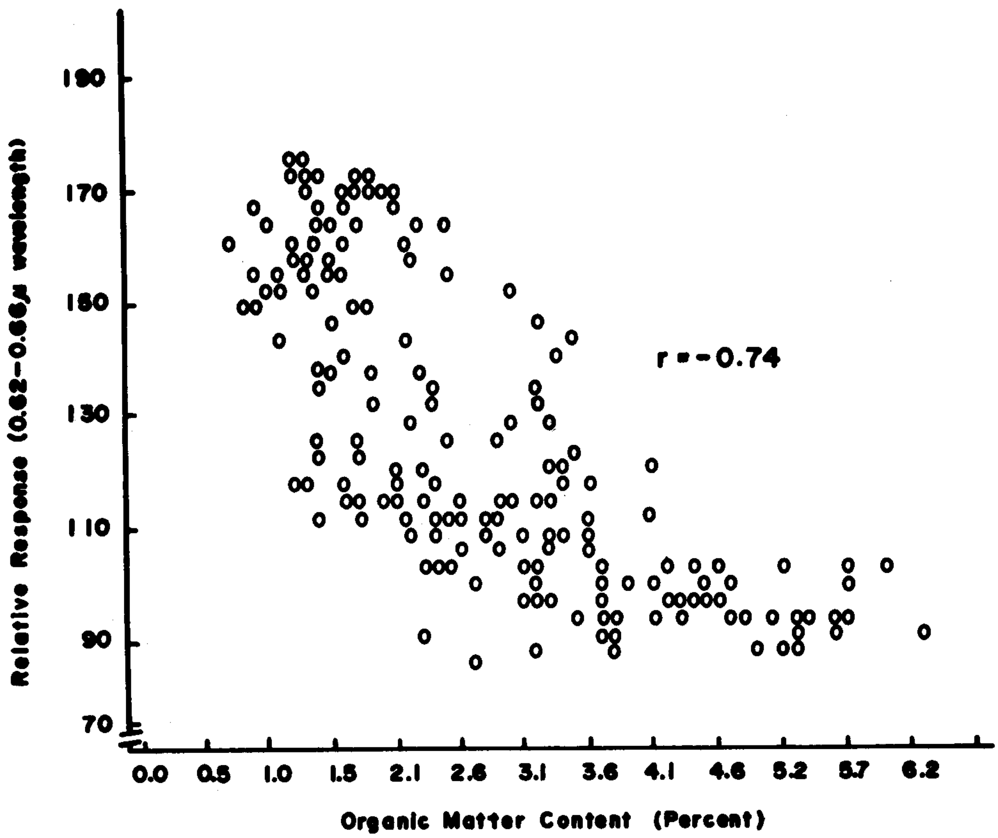

Figure 13. Correlation between average radiance level (relative response) and organic matter content for 197 soil samples in the 0.62-0.66 micron band.

LABORATORY FOR APPLICATIONS OF REMOTE SENSING
PURDUE UNIVERSITY

MAR 20,1970

CLASSIFICATION STUDY .. SERIAL NO. 319005914
CLASSIFICATION DATE .. MAR 19,1970

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TAPE NUMBER---- 218 ALTITUDE-- 4000 FEET

CLASSES CONSIDERED

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V	CL2	16.800
/	CL3	16.800
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F	CL5	16.800
H	CL6	16.800
Z	CLASS 7	16.800
N	CL8	16.800
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FEATURES CONSIDERED

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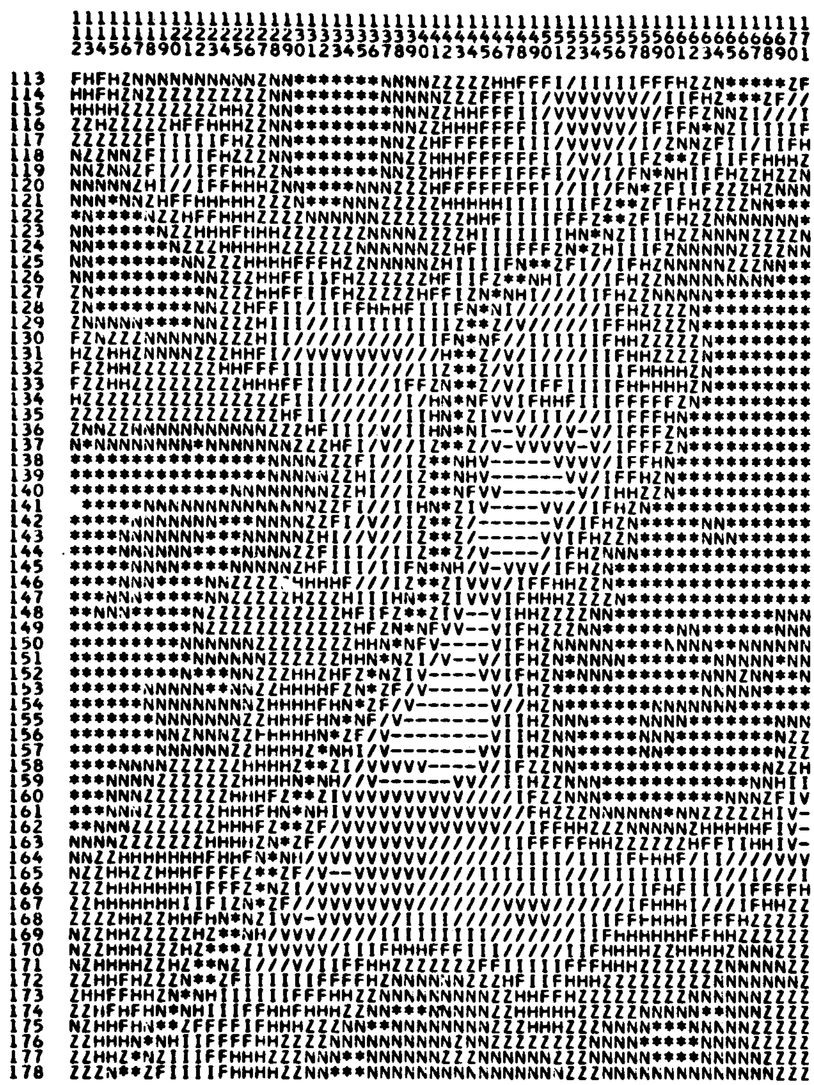


TOTAL NUMBER OF SAMPLED POINTS = 3960

Figure 14. Computer map by organic content of the area around Dieterle Farm. Training samples were those from the study area.

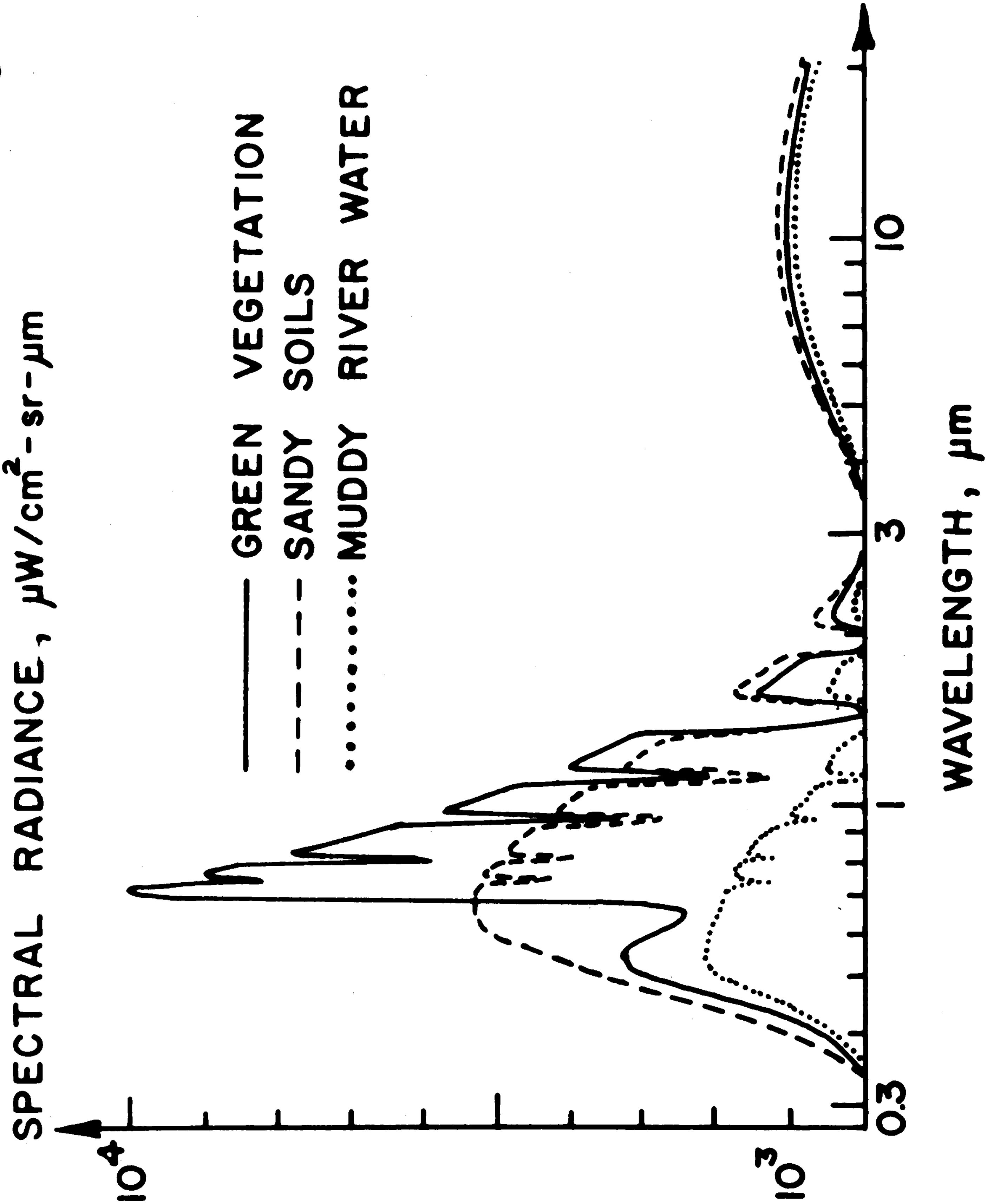


Figure 15. Spectral radiance response curves for green vegetation, sandy soils and muddy river water.

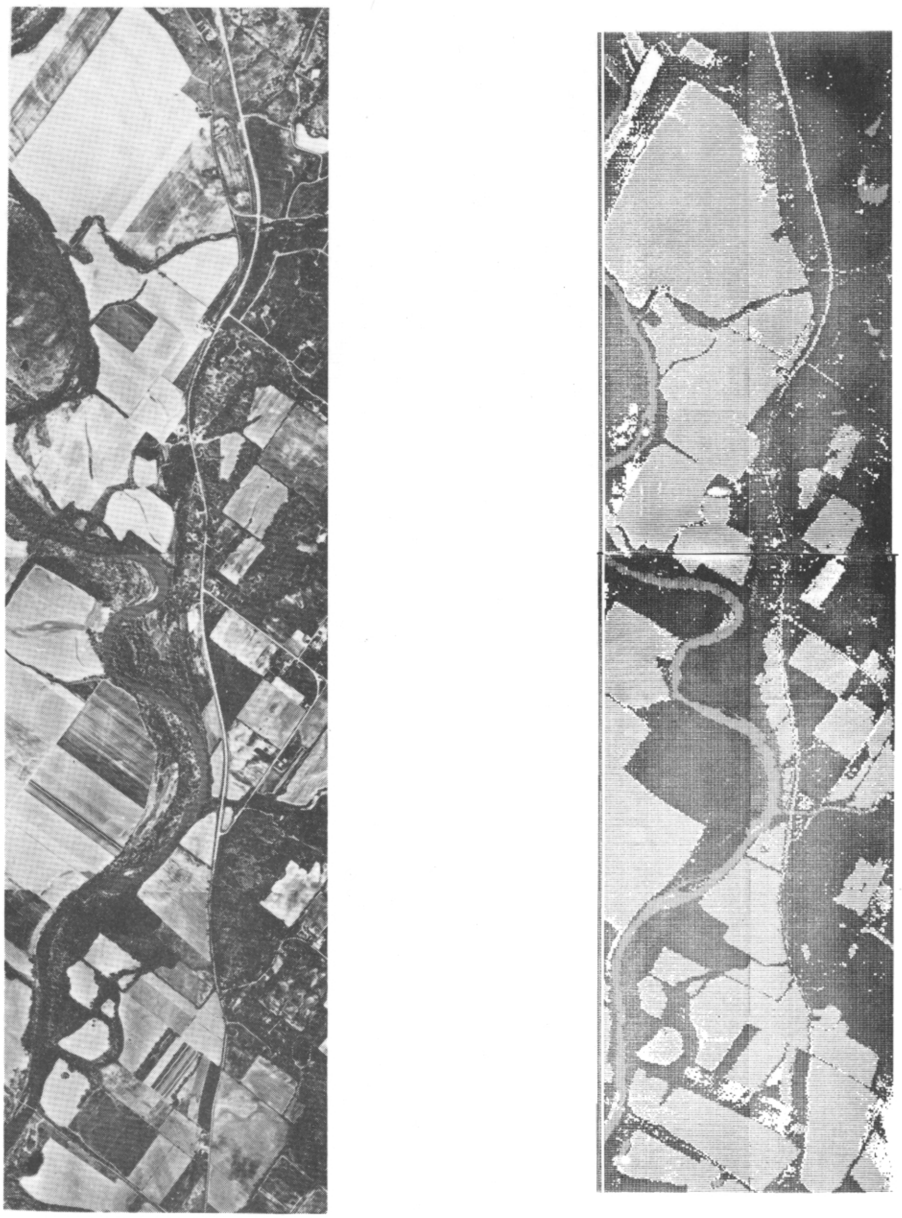


Figure 16. Photograph and computer printout of green vegetation, soil and water of an area in central Indiana.

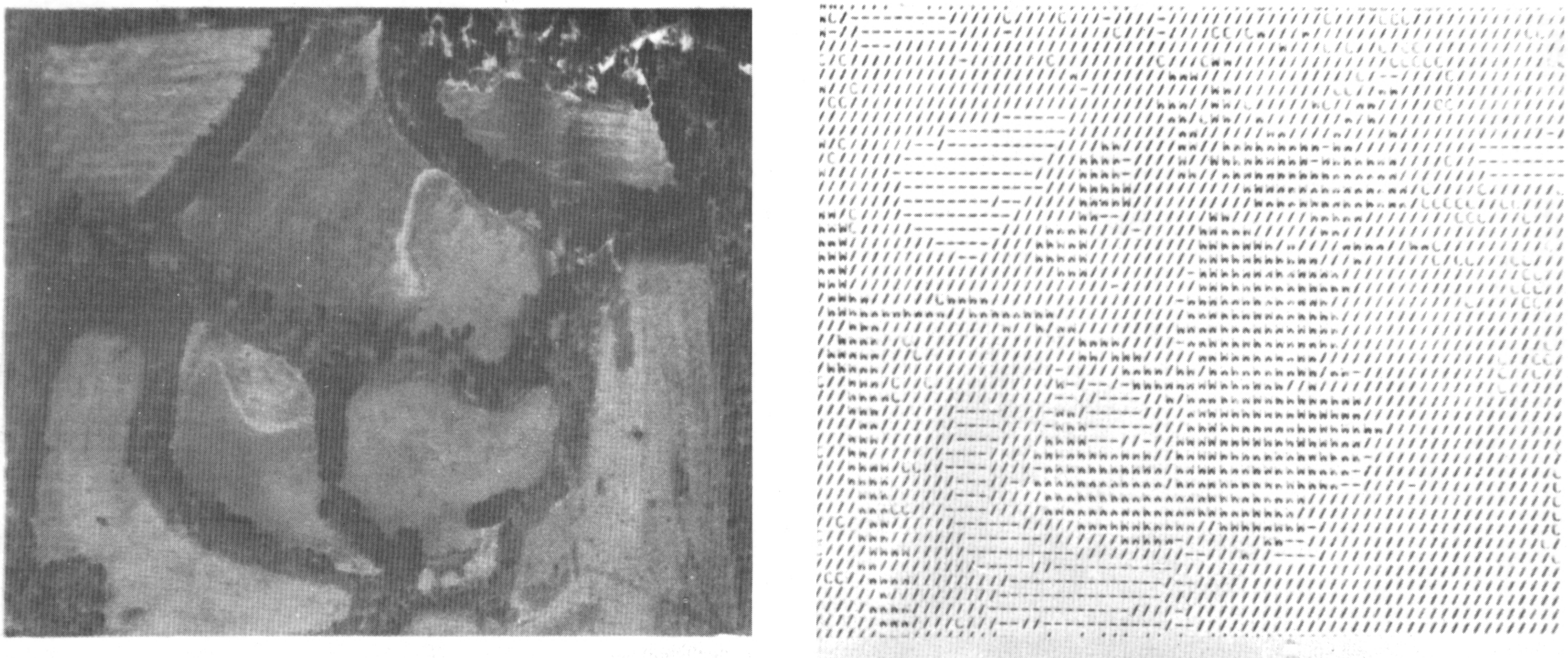


Figure 17. Photograph and computer printout of an area inundated with water.

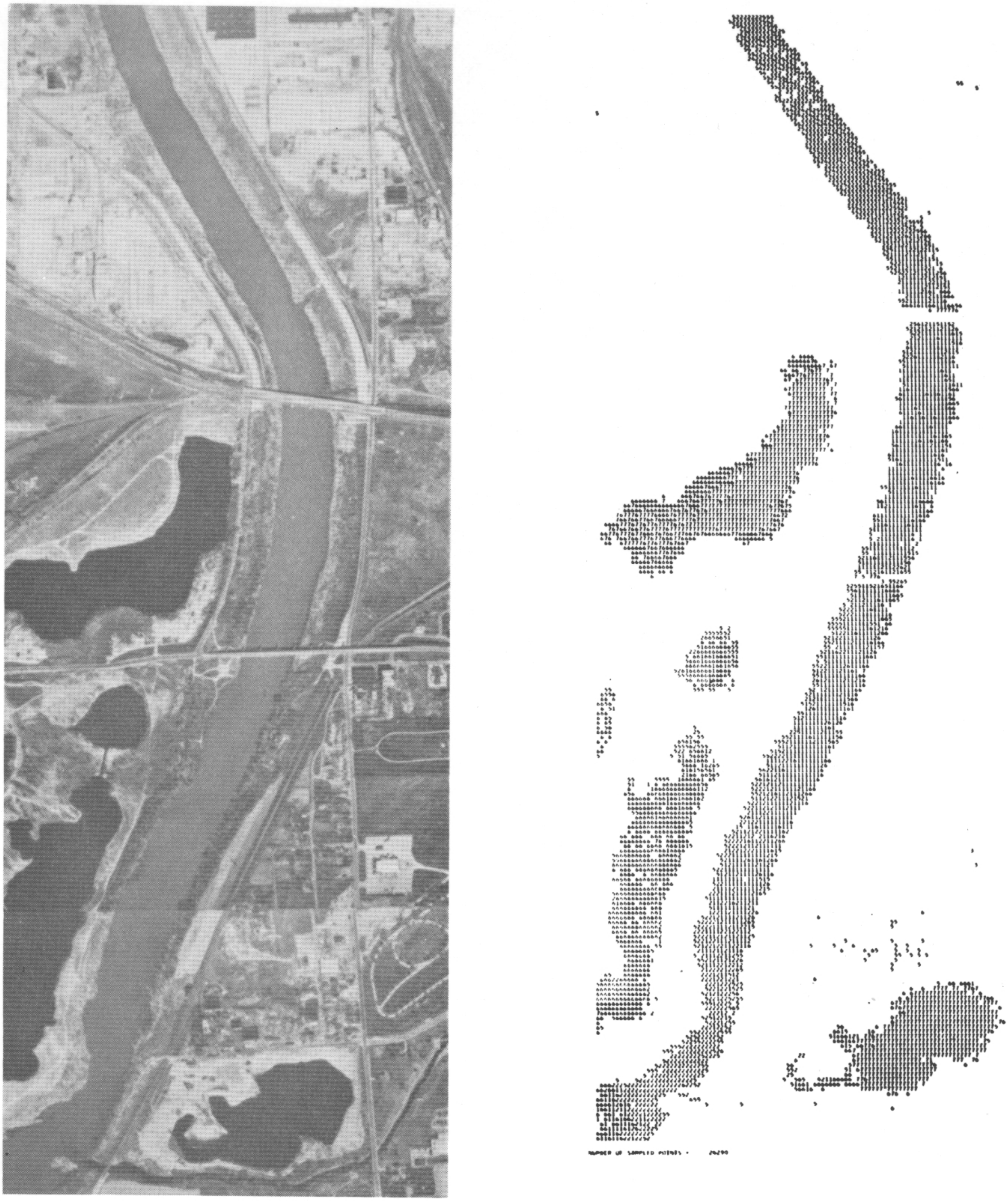


Figure 18. Photograph and computer printout showing water classified into several categories of White River, Indianapolis.

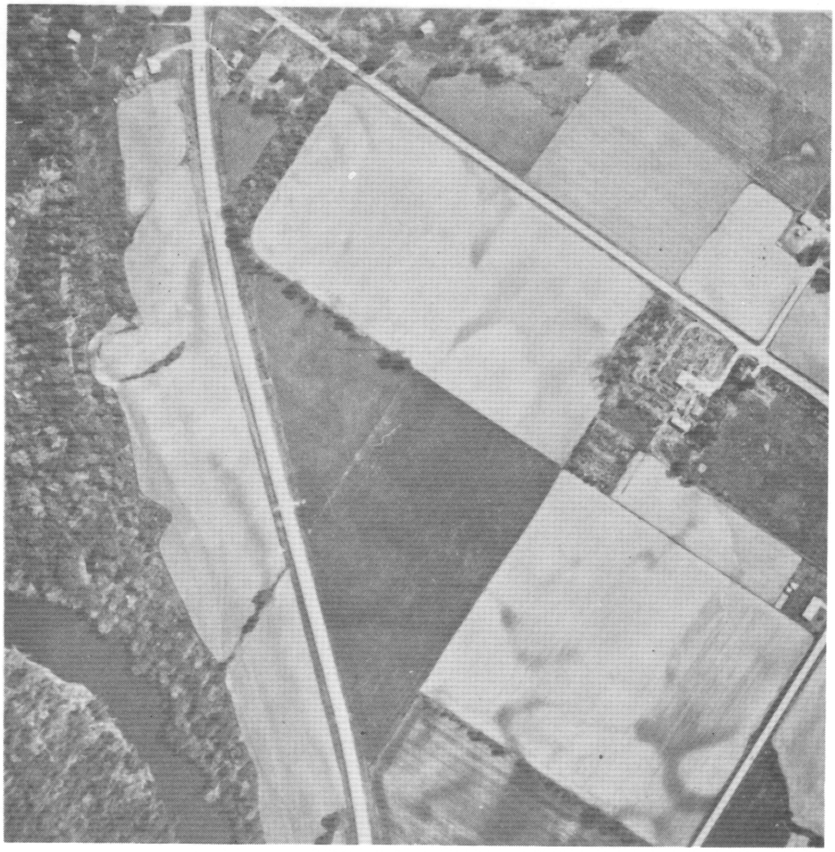


Figure 19, Photograph of study area where different soil color patterns are visible.

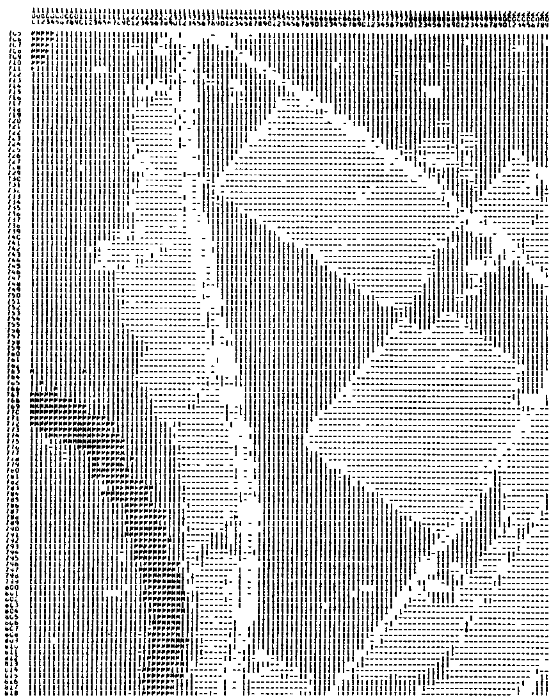


Figure 20. Computer map of green vegetation (I), soil (-) and water (M) for area shown in Figure 20.

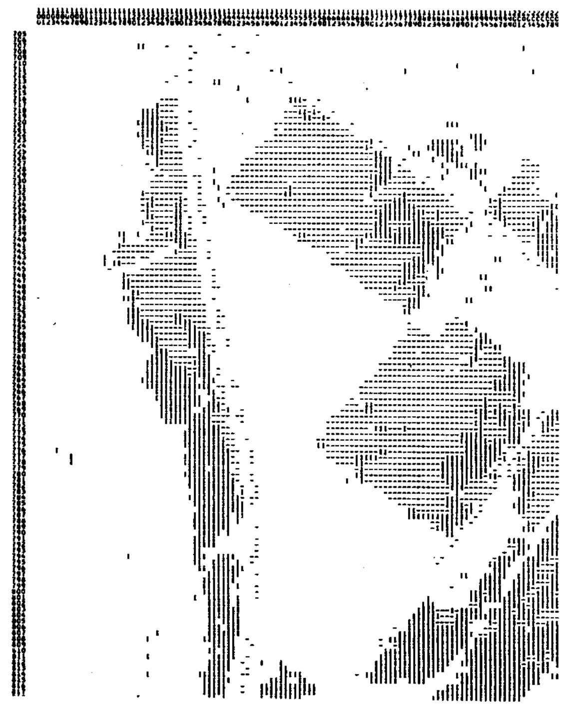


Figure 21. Computer map of the dark and light soil of the area shown in Figure 20.

Figure 22. Computer map of the dark, medium and light soil of the area shown in Figure 20.

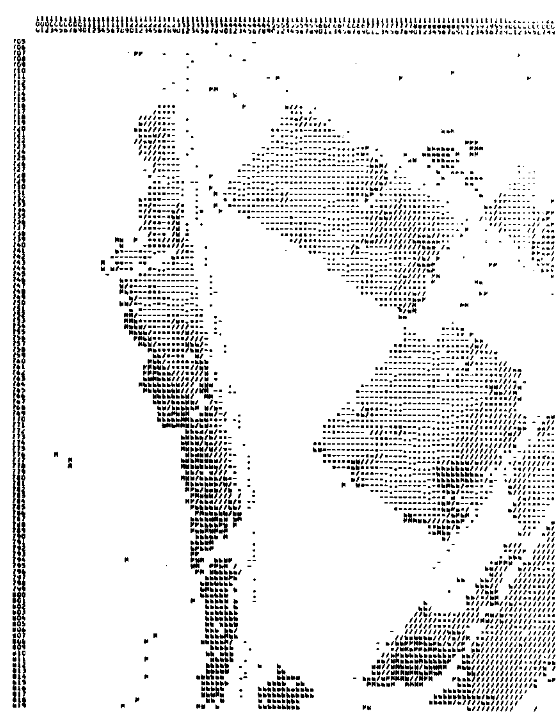


Figure 23. Computer map of six soil categories of the area shown in Figure 20.

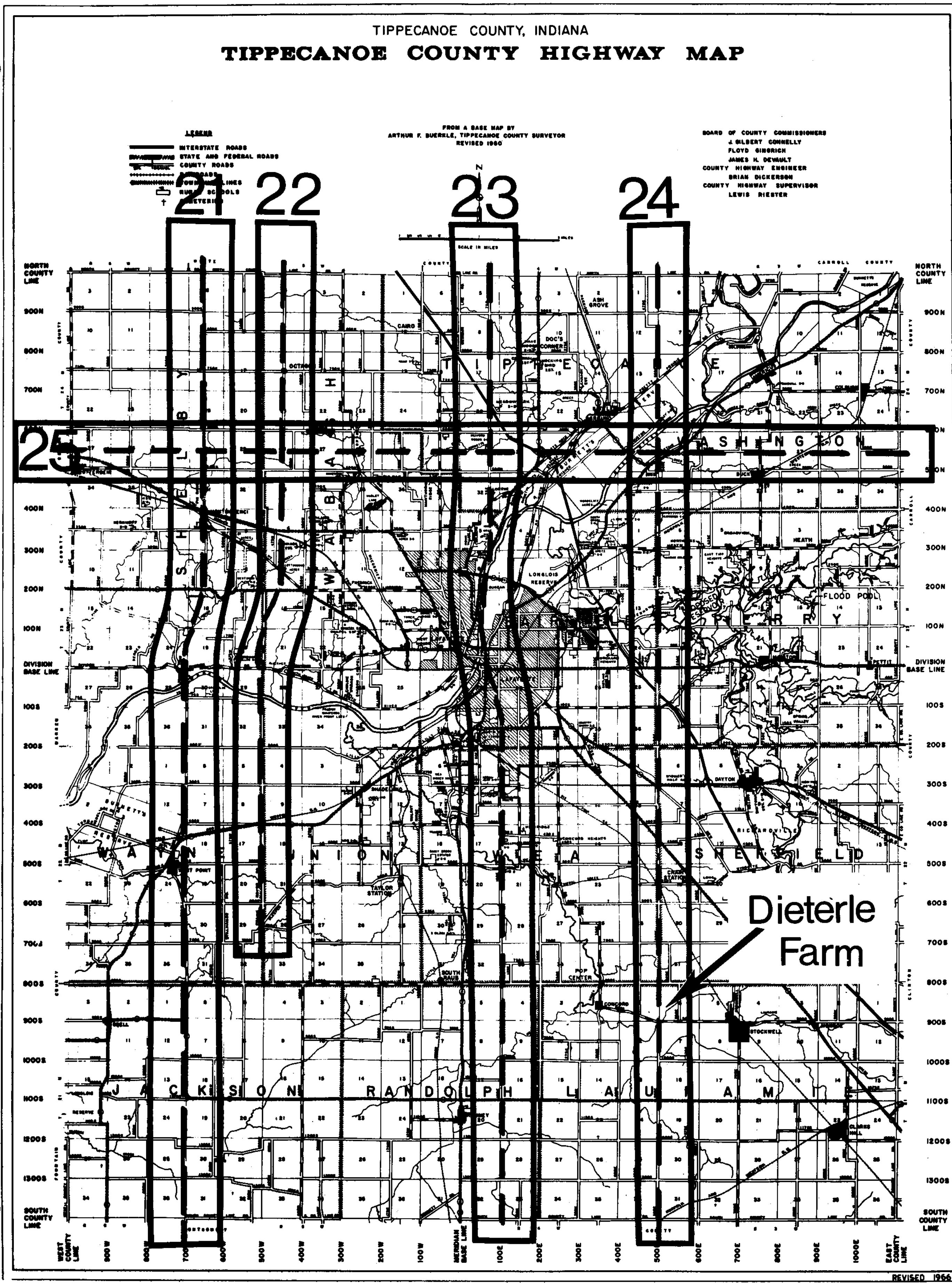


Figure 24. LARS flightlines over Tippecanoe County, Indiana.

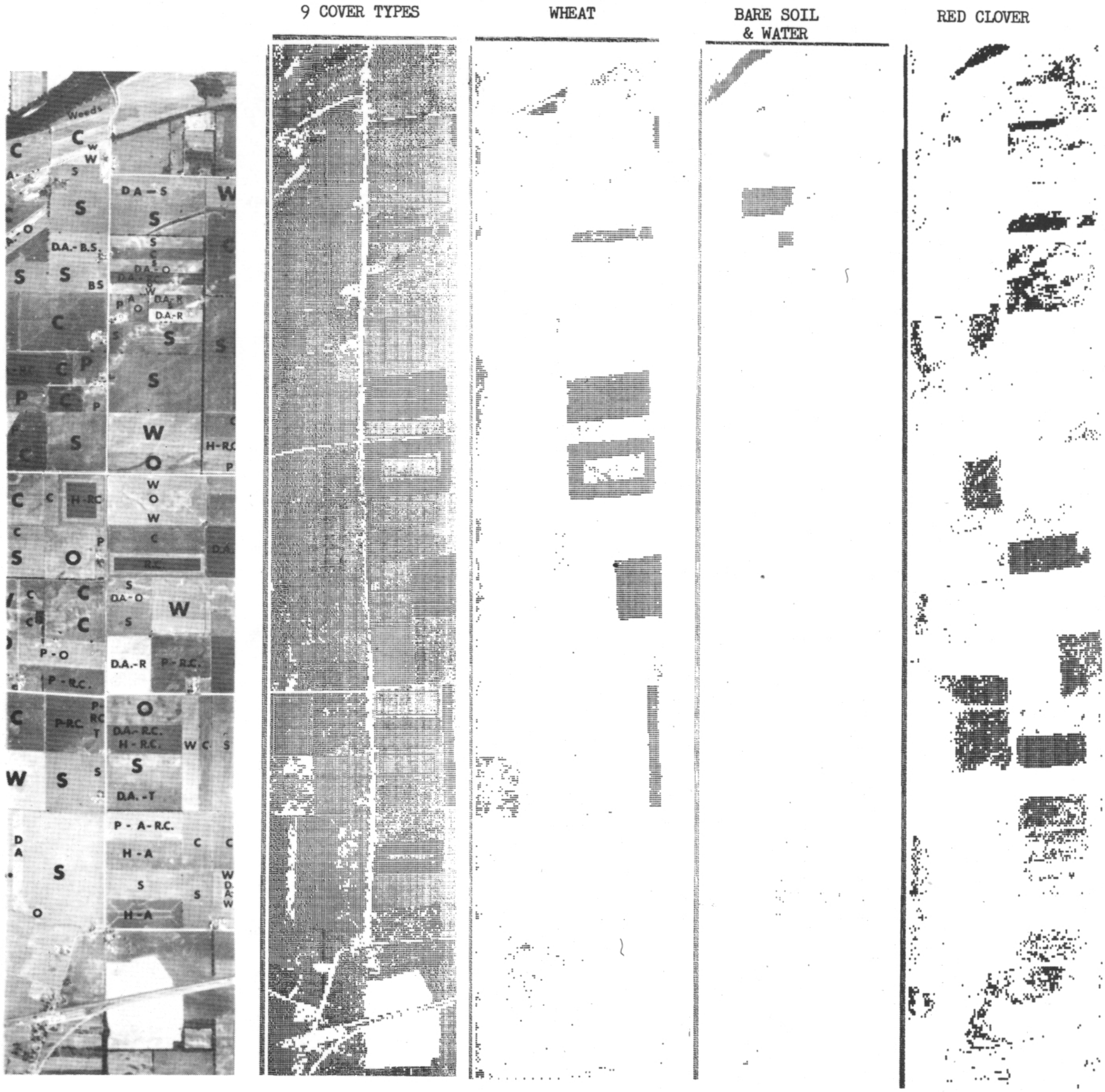


Figure 25. Photograph labeled with symbols denoting ground truth information and computer printouts of 9 cover types, wheat, bare soil and water and red clover.

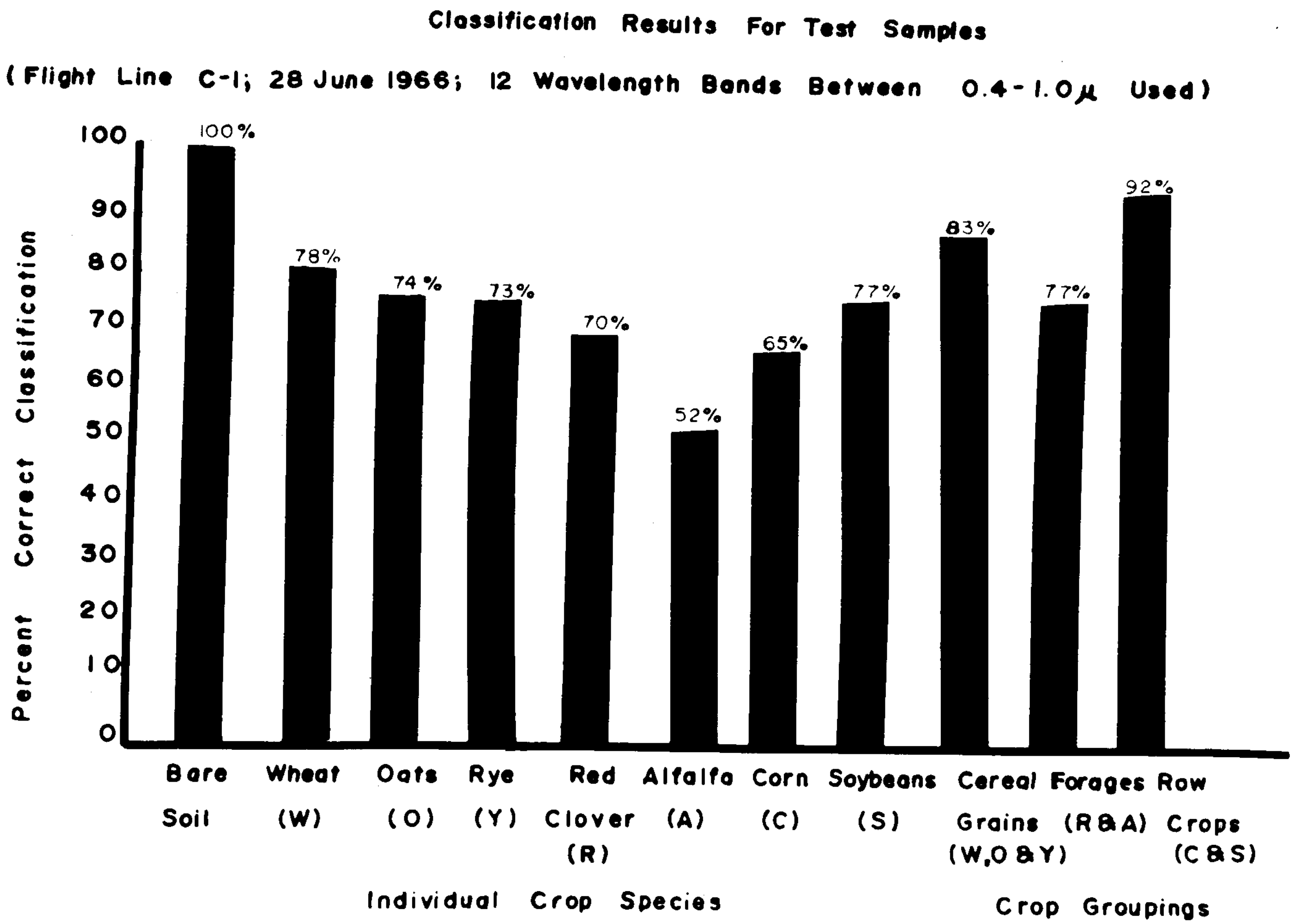
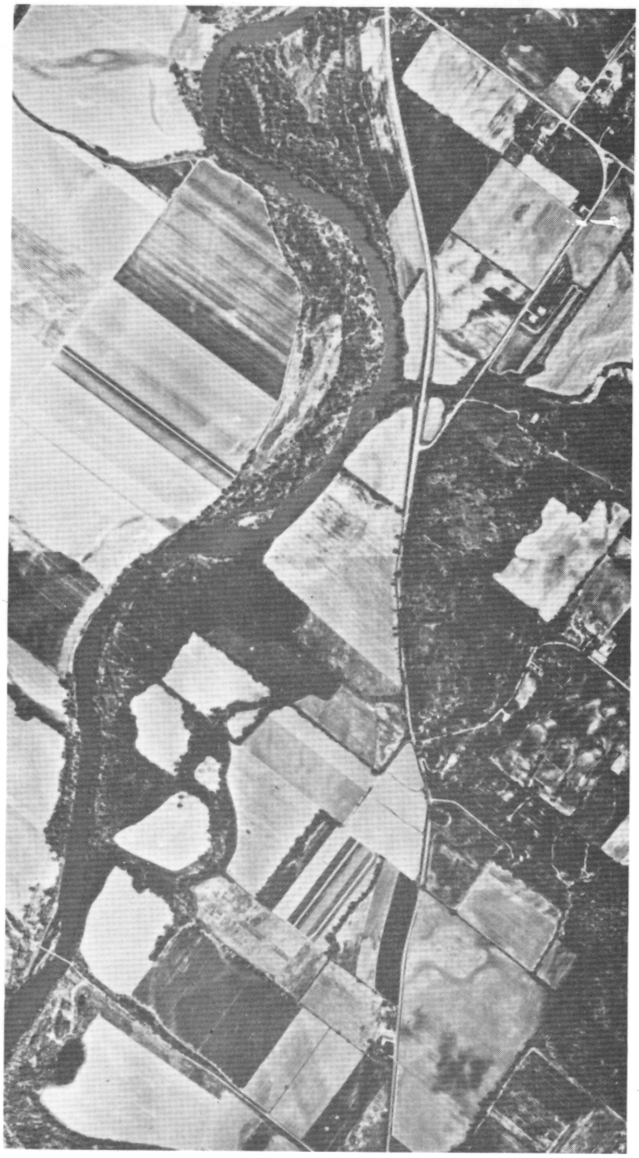


Figure 26. Classification accuracies for analysis shown in Figure 26.

Figure 27. Photograph and computer printouts of row crops and cereal grain categories.



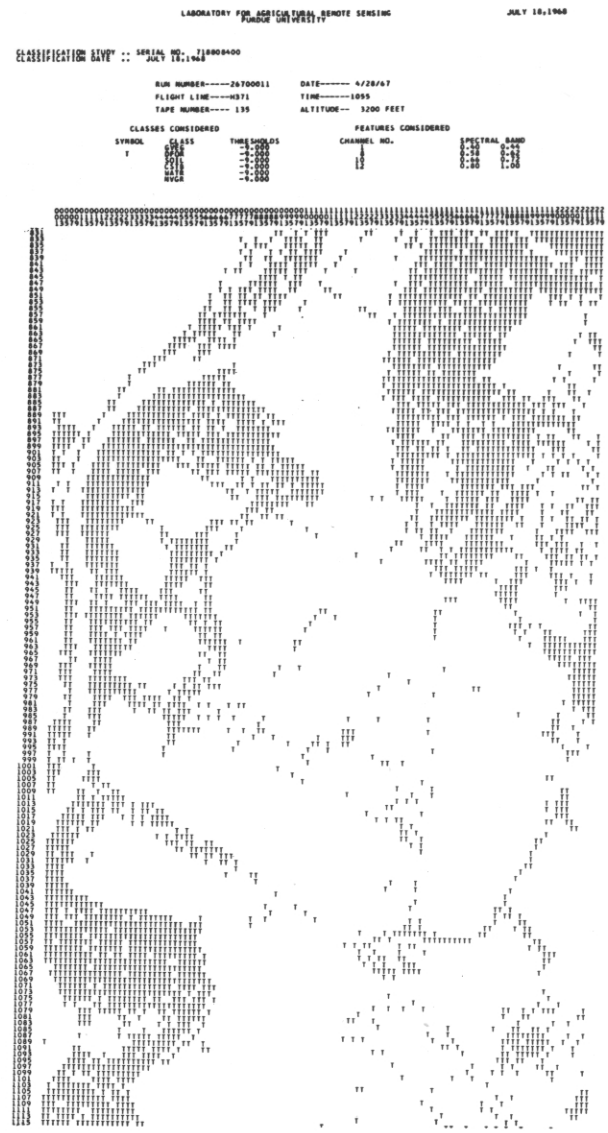


Figure 28. Photograph and computer printout of the deciduous trees.

Figure 29. A 10 level computer printout of the Salton Sea area.

Figure 30. A smaller area from Figure 29 in a 1000 points per inch gray scale printout.

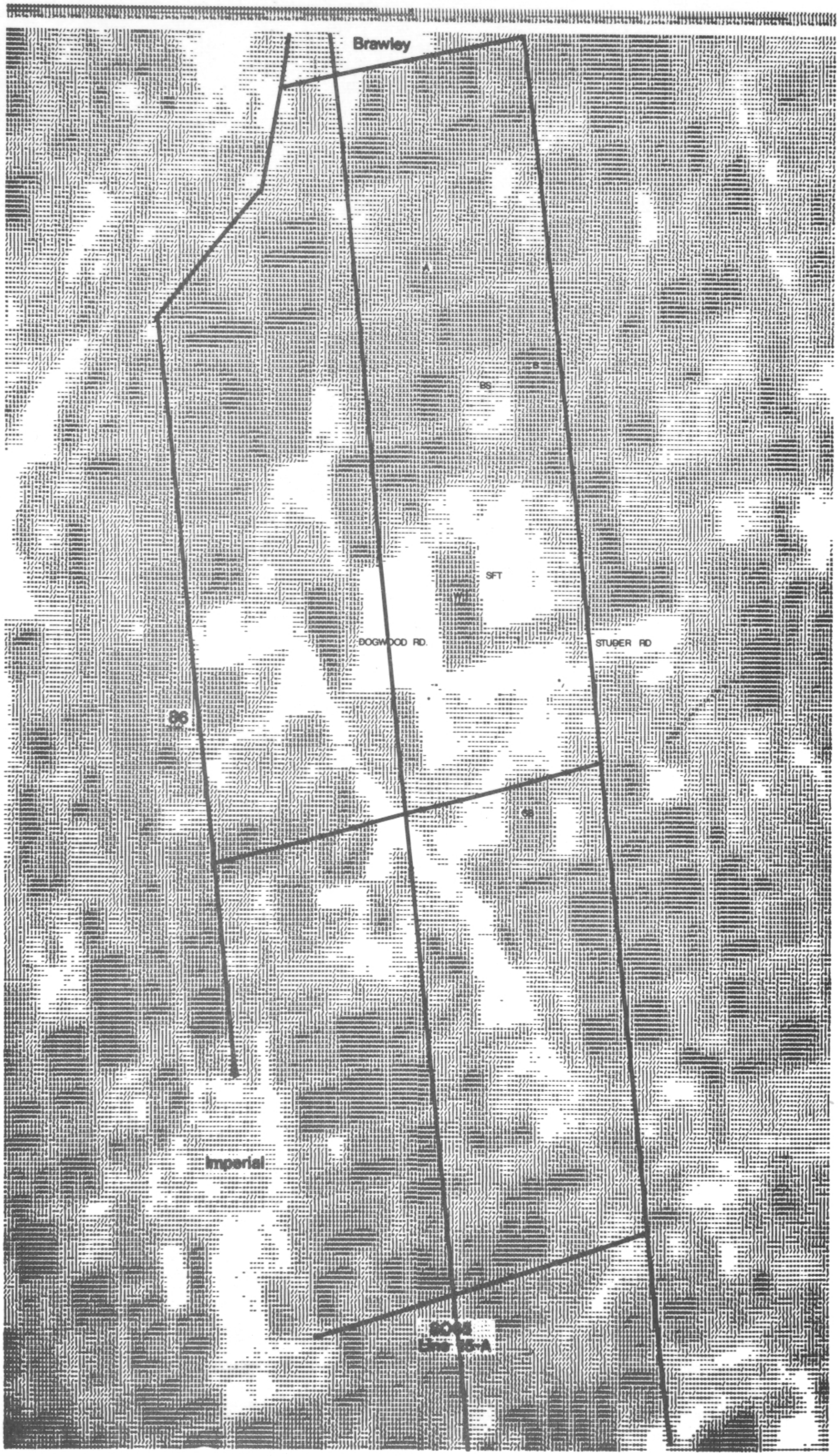


Figure 31. A gray scale printout of 1000 points per inch of Dogwood area.

Figure 32. A classification of the Dogwood area into green vegetation (G), bare soil (-), saline soil (I), and water (W).