SYSTEMS APPROACH

TO THE

USE OF REMOTE SENSING*

by

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ABSTRACT

This paper is a tutorial discussion of earth resources information systems which utilize satellites as sensor platforms. It is begun by pointing out that information may be derived by sensing and analyzing the spectral, spatial and temporal variations of electromagnetic fields eminating from the earth surface. After giving an overview system organization, the two broad categories of system types are discussed. These are systems in which high quality imagery is essential and those more numerically oriented. Sensors are also discussed with this categorization of systems in mind.

The multispectral approach an pattern recognition are described as an example data analysis procedure for numerically oriented systems. The steps necessary in using a pattern recognition scheme are described and illustrated with data obtained from Apollo IX. Both manual and machine-aid training techniques are described for the pattern recognition algorithm.

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Section I

INTRODUCTION: WHAT IS REMOTE SENSING? How is information conveyed?

Imagine that you are high above the surface of the earth looking down on it and that you want to survey the earth's surface in order to learn about its resources and thus to manage them better. How could this information be derived? What must the system to extract it look like?

The field of remote sensing provides some of the answers. Remote sensing is the science and art of acquiring information about material objects from measurements made at a distance, without coming into physical contact with the objects. In remote sensing, information may be transmitted to the observer either through force fields or electromagnetic fields, in particular, through the

- Spectral,
- Spatial, and
- Temporal

variations of these fields. Therefore, in order to derive information from these field variations, one must be able to

- Measure the variation and
- Relate these measurements to those of know objects or materials[1].

If, for example, one desires a map showing all of the water bodies of a certain region of the earth, it is clear that one cannot sense the water directly from spacecraft altitudes, rather only the manifestations of these water bodies which exist at that height. These manifestations, in the form of electromagnetic radiation, must therefore be measured and the measurements analyzed to determine which points on the earth contain water and which do not.

Of the two types of fields mentioned above, electromagnetic fields provide perhaps the greatest potential. The remainder of these remarks will be confined to fields of this type. Figure 1 provides a review of the spectrum of the electromagnetic fields. The visible portion, extending from 0.4 to 0.7 micrometers, is the most familiar to us as it is this portion of the spectrum to which our eyes are sensitive; however, sensors can be built to cover a much broader range of wavelengths. The entire portion from 0.3 to 15 micrometers, referred to as the optical wavelength portion, is particularly of interest. The wavelengths shorter than 0.4 micrometers are in the ultraviolet region. The portion above the visible spectrum is the infrared region, with 0.7 to approximately 3 micrometers referred to as the reflective infrared and the region from 3 to 15 micrometers called the emissive or thermal infrared region. In this latter portion of the spectrum, energy is emitted from the body as a result of its thermal activity or heat rather than being reflected from it.

In addition to the optical wavelengths, the microwave range is also useful in remote sensing. Preliminary results using both passive microwave and radar sensors indicate considerably promise for this microwave portion of the spectrum. For reasons of simplicity and in the interest of time, however, we shall limit our considerations in the remainder of this discussion to the optical portion of the spectrum.

Figure 2 is a diagram of the organization of an earth survey system. It is necessary, of course, to have a sensor system viewing that portion of the earth under consideration. There will necessarily be a certain amount of on-board data processing. This will perhaps include the merging of data from other sources such as sensor calibration and data about where the sensor was pointed.

One must next transport the data back to earth for further analysis and processing. This may be done through a telemetry system, as will be the case for the Earth Resource Technology Satellite, or through direct package return, as will be used with SKYLAB. There usually then is a need for certain preprocessing of the data before the final processing with one or more of the data reduction algorithms. It is at this point in the system, when the data is reduced to information, that it is usually helpful to merge ancillary information, perhaps derived from sources on the surface of the earth.

An important part of the system which must not be overlooked is indicated by the last block in

Figure 2, that of information consumption, for there is no reason to go through the whole exercise if the information produced is not to be used. In the case of an earth resource information system, this last portion can prove to be the most challenging to design and organize since many potential consumers of this information are not accumstomed to receiving it from a space system and may indeed know very little about the information-providing capabilities.

Before leaving the matter of the organization of an information system, the necessity of having a thorough understanding of the portion of the system preceding the sensor must be pointed out. Consider Figure 3. This figure shows a simplified version of the energy exchange in a natural environment. It is possible, of course, to detect the presence of vegetation on the earth's surface by measuring the reflected and emitted radiation emanating from the vegetation. One must understand, however, that there are many experimental variables active. For example, the sun provides a constant source of illumination from above the atmosphere, but the amount of radiation which is reflected from the earth's surface depends upon the condition of the atmosphere, the existence of surrounding objects, and the angle between the sun and the earth's surface as well as the angle between the sun and the earth's surface as well as the angle between the earth's surface and the point of observation. Even more important is the variation which will exist in the vegetation itself. It is possible to deal with these experimental variables in several ways. We shall touch briefly on this point later in the discussion.

Summarizing, then, it is possible to derive information about the earth's surface and the condition of its resources by measuring the spectral, spatial, and temporal variations of the electromagnetic fields emanating from points of interest and then analyzing these meaaurements to relate them to specific classes of materials. To do so, however, requires an adequate understanding of the materials to be sensed and, in order to make the information useful, a precise knowledge is required about how the information will be used and by whom.

Section II

THE DUALITY OF SYSTEMS TYPES: When we consider the state-of-the-art of remote sensing today, a duality of system types becomes readily apparent. Development in the field has had two major stems since it originated from two somewhat different types of technology. These two types of systems will be referred to here as those with

- Image orientation, and
- Numerical orientation

An example of an image-oriented system might be simply an aerial camera and a photointerpreter. The photographic film is used to measure the spatial variations of the electromagnetic fields, and the photointerpreter relates these variations to specific classes of surface cover. Numerically-oriented systems, on the other hand, tend to involve computers for data analysis. Although the photointerpreter and the computer, respecitvely, tend to be typical in the two types of systems, it would be an oversimplification and indeed incorrect to say that they are uniquely related to these systems types. This becomes clearer upon further examination.

Figure 4 compares the organization of the two system types. Both types of systems need a sensor and some preprocessing; however, the distinction between the types can perhaps be brought out most clearly by noting the location of the form image block in the two diagrams. In the image-oriented type, it is in line with the data stream and must precede the analysis block. Numerically-oriented systems, on the other hand, need not necessarily contain a form image block. If they do, and in Earth Resources they usually do, it may be at the side of the data stream, as shown. It may thus be used to monitor the operation of the system and perhaps to do some special purpose analysis as needed. An image is, of course, the most efficient way to convey a large amount of information to a human operator. As seen, this is its principal use in both types of systems, but the use is different in the two cases.

In considering the design of information gathering systems, it is of great importance that the type of sensor as well as the means of analysis to be used are well mated to the type of system orientation. Thus, let us briefly consider the types of imaging space sensors available.

Perhpas the single most distinguishing characteristic of earth resources information systems is that a very large amount of data can be, and indeed must be, gathered in order to derive the desired information. Since an image is a very efficient way to communicate large quantities of data to man, let us arbitrarily restrict ourselves to sensors which are capable of creating images. Shown in the table below is a categorization of imaging sensors into three broad classes: Photographic, television, and scanner. The table also provides example advantages and disadvantages of each.

In the case of photography, the great advantage, of course, is the very high spatial resolution which can be achieved, but to maintain this high resolution, data return by direct package return is required. Also, photography as a sensor is useful only in the visible and in a small part of the reflective infrared portion of the spectrum.

Television has the advantage that the signal occurs in electrical form and thus is immediately ready to be transmitted back to the earth; storage of the data, however, is not inherently present in the system in a permanent form, as it is in the case of photography. Thus, for space systems purposes one is not necessarily faced with the task of carrying along a large quantity of the storage media (photographic film for the photography case) when using a television sensor. One may view this advantage either as an advantage of size and weight or as one of efficiency in that a satellite may be operated a very long time

SENSOR TYPE	EXAMPLE ADVANTAGES	EXAMPLE DISADVANTAGES
Photography	Spatial Resolution	Data Return
Television	Size/Weight	Spectral Range
Scanner	Spectral Range	Mechanical Complexity

Types of Imaging Space Sensors

with a single servicing. Television sensors are restricted to approximately the same spectral range as photography, however.

Scanners can be built to operate over the entire optical wavelength range. They can also provide a greater photometric dynamic range. In order to achieve these advantages, however, they tend to be more mechanically complex.

It is important to realize that the advantages and disadvantages here must be considered only as examples since the advantages and disadvantages in any specific instance will depend upon the precise details of the system. General statements are also difficult relative to the type of sensors which will be best for image-oriented and numerically-oriented systems. There is a clear tendency to favor photography for image-oriented systems due to its high spatial resolution capability, while multiband scanners tend to be favored for numerically-oriented systems since they make available greater spectral and dynamic ranges.

The technology for pictorially-oriented systems is relatively well developed. Sensors best suited to this type of system have been in use for some time, as have appropriate analysis techniques. This type of system also has the advantage of being easily acceptable to thé layman or neophyte, an advantage important in the earth resources field since, as it was pointed out above, many new earth resources field since, as it was pointed out above, many new data users are expected. Similarly, it is well-suited for producing subjective information and is especially suited to circumstances where the classes into which the data is to be analyzed cannot be precisely decided upon beforehand. Thus, man with his superior intelligence is or can be, deeply involved in the analysis activity. Pictorially-oriented systems also have the possibility of being relatively simple and low-cost. On the other hand, it is difficult to use them for large scale surveys over very large areas involving very large amounts of data.

In the case of numerically-oriented systems, the technology is much newer and not nearly so well-developed, though very rapid progress is being made. Because the various steps involved tend to be more abstract; they tend to be less readily understandable by the laymen. This type of system is best suited for producing objective information, and large-scale surveys covering large areas are certainly possible. Numerically-oriented systems tend to be generally more complex, however.

In summary to this point, the state of-the-art is such that there are two general types of systems; this duality exists primarily for historical reasons and because of differences of the points from which technology development began. One type is based on imagery, and, therefore, a key goal of an intermediate portion of the system is the generation of high quality imagery. In the other case imagery is less important and indeed may not be necessary at all. It is not appropriate to view these two types of systems as being in competition with one another since they have different capabilities and are useful in different circumstances. These two stems of technology are approaching one another so that the differences between them is becoming less distinct.

We will proceed now to a further consideration of numerically-oriented systems since this type may be less familiar. In particular we shall examine a type of data analysis useful in this case.

Section III

THE MULTISPECTRAL APPROACH AND PATTERN RECOGNITION: In recent years considerable effort has been devoted to what is referred to as the multispectral approach for data analysis. An initial understanding of what is meant by the term "multispectral approach" may be obtained by considering Figure 5. Shown here in the upper left of the figure is a reproduction of a conventional color photograph of a set of color cards. The remainder of the figure shows photographs of the same color cards taken with black and white film and several different filters. The pass band of each filter is indicated beneath the particular color and card set. For example, in the .62-.66 micrometer band, which is in the red portion of the visible spectrum, the red cards appear white in the black and white photo, indicating a high response or a large amount of red light energy being reflected from these cards. In essence the multispectral approach amounts to identifying any color by noting the set of gray scale values produced on the black and white photographs for that particular color rectangle.

As a very simple example of the approach Figure 6 shows images of an agricultural scene taken in three different portions of the spectrum. Note that in the three bands alfalfa has responses which are dark, light, dark respectively whereas bare soil is gary, dark, white. Thus, alfalfa can be discriminated from bare soil by identifying the fields which are dark, light, dark in order in these three spectral bands.

One may initially think of the multispectral approach as one which a very quantitative measure of the color of a material is used to identify it. Color, however, is a term usually related to the response of the human eye; the terminology of spectroscopy which is more precise is more useful in understanding the multispectral approach. Another reason for this is that it is applicable beyond the visible region.

In order to understand this approach and to see how a numerically-oriented system may be based upon it, consider Figure 7. Shown at the top is a graph of relative response (reflectance) as a function of wavelength for three types of earth-surface cover material: vegetation, soil, and water. Let two wavelengths marked λ_1 and λ_2 be selected. Shown in the lower part of this figure is the data for these three materials at these two wavelengths, plotted with respect to one another. For example, in the upper graph soil has the largest response at wavelength λ_1; this manifests itself in the lower plot in the fact that soil has the largest abscissa value (the greatest displacement to the right).

It is readily apparent that two materials whose response as a function of wavelength are different will lie in different portions of the two-dimensional space*. When this occurs one speaks of the materials involved as having unique spectral signatures. This concept will be pursued further presently; however, at this point it is important to recognize that the concept of a spectral signature is a relative one--one cannot know that vegetation has a unique spectral signature, for example, until one sees the plots resulting from the spectral response of other materials within the scene to be analyzed. Note also that a larger number of bands can be used. The response at λ_3 could be used and the data plotted in three dimensions. Four or more dimensions indeed have meaning and utility even though an actual plot of the data is not possible.

So far no spatial or temporal information has been involved, only spectral. Temporal information can be utilized in several ways. Consider Figure 8. Time is always a parameter of the spectral response of surface materials. As an example, consider the problem of discriminating between soybeans and corn. Under cultivation, these two plants have approximately 140-day growing cycles. Figure 8 illustrates what the two-dimensional response plot might be for fields of these two plants with time as a parameter. Upon planting and for some period thereafter, fields of soybeans and corn would merely appear to be bare soil from an observation platform above them. Eventually though, both plants would emerge from the soil and in time develop a canopy of green vegetation, mature to a brownish dry vegetation, and diminish. Thus, as viewed from above the fields of soybeans and corn would, in fact, always be mixtures of green vegetation and soil. In addition to the vegetation of the two plants having a slightly different response, as a function of wavelength, the growing cycles and plant geometrys are different; thus, the mixture parameters might (and in fact do) permit an even more obvious difference between the two plants than the spectral response difference of the plant leaves themselves. This is the implication in Figure 8 as shown by the rather large difference between them 30 days from planting date (partial canopy) as compared to 75 days (full canopy).

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*This space is referred to as feature space.

Thus, one way in which temporal information is used is simply in determining the optimum time at which to conduct a survey of given materials.

A second use of temporal information is perhaps less obvious. Consider the situation of Figure 8 at the 75 days and 100 day point. In this case the separation of the two materials is relatively slight. However, if this data is replotted in four-dimensional space, λ_1 and λ_2 at 75 days as dimensions one and two and λ_1 and λ_2 at 100 days as dimensions three and four, the small separability at the two times can often be made to augment one another.

A third use of temporal information is simply that of change detection. In many Earth Resources problems it is necessary to have an accurate historical record of the changes taking place in a scene as a function of time.

Let us move now to consider how one may devise a procedure for analyzing multispectral data.[3,4] In the process, one further facet of the multispectral approach must be taken into account. The radiation from all soybean fields will not have precisely the same spectral response, since all will not have had the same planting date, soil preparation, moisture conditions and so on. Indeed, response variation within a class may be expected of any earth-surface cover. The extent of response differences of this type certainly has an effect upon the existence of a spectral signature, that is, the degree of separability of one material from another. Consider, for example, a scene composed of soybeans, corn and wheat fields; if five samples of each material are drawn, the two-dimensional response patterns might be as shown in Figure 9 indicating some variability exists within the three classes. Suppose now an unknown point is drawn from the scene and plotted, as indicated by the point marked U.

The design of an analysis system in this case comes down to partitioning this two-dimensional feature space in some fashion, such that each such possible unknown point is uniquely associated with one of the classes. The engineering and statistical literature of the world abounds with algorithms or procedures by which this can be done.[5,6] One very simple one is shown in Figure 10. In this case the conditional centroid or center point of each class is first determined. Next the locus of points equidistant from these three centroids is plotted and results in the three segments of straight lines as shown*. These lines form, in effect, decision boundaries. In this example the unknown point "U" would be associated with the class soybeans as a result of the location of it with respect to the decision boundaries.

This technique of analysis is referred to as pattern recognition, and there are many more sophisticated procedures resulting in both linear and nonlinear decision boundaries. However, the procedure

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*When more than two dimensions (spectral bands) are being used, note that this locus would become a surface rather than a line.

of using a few initial samples to determine the decision boundaries is common to a large number of them. The initial samples are referred to as training samples, and the general class of classifiers in which training samples are used in this way are referred to as supervised classifiers.

Up to this point, the implication has been that photography or multispectral photography is the sensor to be used in generating data for this type of an analysis procedure. While indeed this data source can be used, a perhaps more appropriate one is a device known as a multispectral scanner. Figure 11 diagrams such a device as might be mounted in an aircraft.

Basically the device consists of a multiband spectrometer whose instantaneous field of view is scanned across the scene. The scanning in this case is accomplished by a motor-driven scanning mirror. At a given instant the device is gathering energy from a single resolution element. The energy from this element passes through appropriate optics and may, in the case of the visible portion of the spectrum, be directed through a prism. The prism spreads out the energy according to the portion of the spectrum; detectors are located at the output of the prism. The output of the detectors can then be recorded on magnetic tape or transmitted directly to the ground. Gradings are commonly used as dispersive devices for the infrared portion of the spectrum.

A most important property of this type of system is that all energy from a given scene element in all parts of a spectrum pass through the same optical aperture. Thus, by simultaneously sampling the output of all detectors one has, in effect, determined the response as a function of wavelength in each spectral band for the scene element in view at that instant.

Of course, the scanning mirror causes the scene to be scanned across the field of view transverse to the direction of platform motion, and the motion of the platform (aircraft) provides the appropriate motion in the other dimension so that in time every element in the scene has been in the instantaneous field of view of the instrument.

As an example of the use of this type of sensor and analysis procedure, reaults of the analysis of a flightline will be presented in brief form*. The particular example involves the classification of a one-mile by four-mile area into classes of agricultural significance. Four-dimensional data (four spectral bands) were used for the classification and the actual classification scheme is known as maximum likelihood discrimination.[4] The data are shown in Figure 12 along with a conventional panchromatic air photo of the scene in which the correct classification of each field has been added to the photo by hand. The symbols on the air photo and their associated classes are as follows: S - soybeans, C - corn, O - oats, W - wheat,

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*This example was originally generated by Professor Roger Hoffer of LARS/Purdue.

A - alfalfa, T - timothy, RC - red clover, R - rye, SUDAN - sudan grass, P - pasture, DA - diverted acres, and H - hay.

Figure 13 shows the results of the classification. Two simple classes are shown. All points of the scene classified as row crops (either corn or soybeans) are indicated in the center of the figure. On the right are indicated all points classified as cereal grains (either wheat or oats).

A quantative evaluation of the accuracy was conducted by designating for tabulation the correct class of a large number of fields in the flightline. The result of this tabulation is shown in Figure 14. It is seen that all results for all classes are above 80% correct.

The same procedures using aircraft data have been utilized for a wide number of classification tasks in addition to crop species identification. Some of these are as follows: Tests of agricultural and engineering soils, mapping and delineating soil types, mineral content, organic content and moisture content of the soil; geologic feature mapping; water quality mapping and mensuration using both reflective and emissive spectra; forest cover identification and tree species delineation; and delineation into geographic and land-use mapping categories.

Section IV

SOME PROCEDURAL DETAILS IN THE USE OF PATTERN RECOGNITION: With the basic concept of pattern recognition in mind, it is possible to proceed to some further details on how it may be applied. One of the most important of these details is the definition of the classes into which the data are to be categorized.

There are two conditions that a class must meet in order to be useful. The class must be separable from all others and it must be of informational value. For example, it does no good to define a class called iron ore deposits if the spectral response which iron ore provides is not sufficiently distinct from all other earth-surface materials over which data are to be gathered. On the other hand, if no one is interested in locating the iron ore deposits within the region to be surveyed, there is no reason to define such a class. We shall see presently that one may name classes of informational value and then check their separability, or vice versa.

A second matter is determining the point at which a class actually becomes defined. In an agricultural survey, simply naming a class soybeans does not define it precisely enough. For example, what percent ground cover is required before a given resolution element should have its classification changed from bare soil to soybeans? What percent of a resolution element may be covered with weeds and so on? The fact of the matter is that the class becomes precisely defined only by the training samples to be used for it. Thus, an important step in the procedure is the selection of training samples which are sufficiently typical of the whole class in question.

One must also recognize that the definition of a class is always a relative matter. That is, it is relative to the other classes used in the same classification. The effect of the decision boundaries is to divide up the feature space (see Figure 9) into non-overlapping regions depending on the relative location of the class training sets relative to one another.

It should also be noted, however, that as a result, every point in the space automatically becomes associated with one of the named classes. It is therefore necessary that the list of classes be exhaustive so that there is a logical class to which every point in the scene to be analyzed may be assigned.

As a result of these factors it is apparent that the selection of training samples is especially important. There are two approaches to obtaining training data; we shall refer to them here as the signature bank approach and the extrapolation mode.

Using the signature bank approach, the researcher first decides on a list of appropriate classes and then draws from a signature bank previously collected data on the classes of material identical to those selected. This approach has a considerable amount of aesthetic appeal. Presumably one could accumulate a very large bank of data from typical classes and thereafter always have training data available for any situation without further effort.

However, such an approach would place stringent constraints on the sensor system since absolute measurements of scene radiance would be necessary if they are to be referenced to a future data-gathering mission. Further, the extent to which detailed and sophisticated classes could be utilized would be limited by the ability to determine and adjust for the instantaneous values of all the other experimental parameters, such as the condition of the atmosphere, the sun and view angle, possible seasonal variations in the vegetation, the natural statistical distribution of the data for various classes, etc. In short, while such a procedure is possible, it will result in more stringent requirements on the sensor system and considerably data preprocessing in order to achieve this maximum utility. Alternatively, it would have to be restricted to cases in which only relatively simple classes were necessary.

The extrapolation mode, on the other hand, has somewhat different characteristics. In this case, training data for each of the classes are obtained by locating within the data to be analyzed specific examples of each of the classes to be utilized. The classification procedure, therefore, will amount to an extrapolation from points of known classification within the scene to the remaining portions of the data. This approach has the advantage of requiring less exactness in the calibration capability of the sensor system and in the knowledge of the other experimental variables since only variation of these factors within the data gathering mission, and not those from mission to mission must be accounted for. On the other hand, it has the disadvantage of requiring some knowledge about the scene to be analyzed before the analysis can proceed. In the case of populated or accessible areas, this knowledge usually comes from ground observations. In the case of inaccessable areas as well as accessable and/or populated ones, it could perhaps also come from a very limited, low-altitude aircraft mission. The relative cost of this additional information often turns out to be low. The extrapolation mode was used in both the preceding example and the one to follow.

To illustrate these details and procedures, an example follows in which a pattern-recognition scheme was trained and then used to classify a relatively large amount of data. Data for this experiment were collected aboard the Apollo 9 space vehicle as a part of the experiment known as S065. This example was selected because in addition to illustrating the steps described above, it provides the first indication of how these techniques may perform on space data.[7,8] Both the ground resolution and the spectral resolution of this data are similar to those which will be obtained by the Earth Resources Technology Satellite; however, since the S065 experiment involved photographic sensors, the results obtained may be on the conservative side of those from ERTS since, as previously indicated, photography does not ordinarily provide the optimal type of data for this analysis procedure. Further, since the sensors were photographic, some preliminary processing steps to prepare the data for analysis were necessary. These steps involved first scanning the photography (on a rotating drum microdensitracer) to convert it to digital form, then bringing the images gathered over the same scene in the different spectral bands into spatial alignment with one another.[9,10] These steps are not typical and are beyond the scope of the discussion at hand. We will proceed from the point at which the preprocessing steps provided four-dimensional (four spectral bands) data for analysis. The four spectral bands involved were .47 to .61 micrometers, .59 to .715 micrometers, .68 to .89 micrometers, and .51 to .89 micrometers. These bands were determined by the film and filter combinations used on the four cameras.

Figure 15 shows a color infrared version of the particular frame used, a portion of Southern California, Arizona, and Northern Mexico. In the lower left of the irrigated area of very great importance agriculturally. Also shown in the figure is a computer-generated gray scale printout of one band of the data. The scene covers about 10,000 square miles and contains about five million points.

In order to test the separability of various classes, two analysis tasks were carried out. The first, involving agricultural classes, was carried out in the area designated by the small rectangle in the lower left of the printout. Figure 16 shows a high resulution printout of the same area. The individual fields of the scene are clearly evident in this printout. To begin with some relatively simple classes were defined. These were given vegetation, bare soil, water, and salt flats. Figure 17 shows the result of classifying the data into these categories. The accuracy of this classification was judged to be very high and as a result it was decided to attempt a classification with more detailed categories. The result of this classification is shown in Figure 18. It is seen that the classes used were barley, alfalfa, sugar beets, bare soil, salt flat, and water. A quantative assessment of the accuracy in this case indicated an average accuracy of approximately 70%.

The second analysis task carried on this data set was done over the whole frame. Classes of geologic interest was defined in this case and an attempt was made to achieve what amounts to as a geologic map of the area. The result of this classification is shown in Figure 19. Some, but not all, of the classes used are indicated at the bottom of this figure. The results of this classification was compared with existing geologic maps of the area by a professional geologist, and again the results were judged to be highly satisfactory.

Now with an overview of the experiment and the results achieved in mind, let us examine the procedures used to obtain the results. In the case of an agricultural problem the classes of interest usually exist in well defined fields. It is thus, realtively easy to locate sample fields of each class from which to draw training samples. In this case, ground observations from a relatively small region on the ground can be used to derive a sufficient number of training samples for each class. The number of training samples necessary for each class depends upon the number of spectral bands to be used among other things. But generally no more than a few hundred are required, fewer in simpler situations. Thus, Figure 20 depicts a typical situation for this type of classification. The fields outlined here are a typical set of training fields for such a classification task.

The classification of a natural area presents a slightly different situation, however. In this case it may be more difficult to manually locate training samples since boundaries between different materials will be more difficult to locate. Over the last year or tow research has been directed towards samples in the circumstance: One such procedure involves the use of a type of classifier not utilizing training samples and thus referred to as an unsupervised classifier. The basic idea behind nonsupervised classifiers becomes apparent by considering the next several figures.

Assume that one has some two-dimensional data as shown in Figure 21. Assume also that one knows there are three classes of material represented in this data, but the correct association of the individual points with the three classes is unknown. The approach is to initially assume that the three classes are separable and check this hypothesis subsequently.

There are algorithms (computational prodedures) available[11,12,13] which will automatically associate a group of such points with an arbitrary number of mode centers or cluster points. These procedures, known as clustering techniques, can be used to so divide the data and the result of applying such a procedure might be as shown in Figure 22.[14] There remains, then, the matter of checking to be sure that the points assigned to a single cluster all belonged to the same class of material. In passing it is worth noting a comparison between supervised and non-supervised classifiers. In the supervised case, one generally names classes of informational value and then checks to see if the clusters resulting are indeed associated with the classes of informational value.

Figure 23 shows the result of applying such a clustering technique to some multispectral data. The algorithm was instructed to form five cluster points. Comparison of the clustering results with the data in image form shows that the clusters indeed were associated with individual fields. Cluster four, for example, was associated with fields in the upper left and lower right, clusters two and three with the field in the lower left, and so on. Such a technique is used to speed the training phase of the classifier by aiding the human operator in obtaining points grouped according to the class that they came from; the statistics of each cluster point can be immediately computed from the clustered results so that decision boundaries are located. The operator is thus relieved of the necessity of locating and separating individual fields for training each class.

The value of such a procedure is even greater in cases where the boundary between classes is not so distinct in the data. Figure 24 shows the result of clustering data for a soils mapping classification. Here it would be more difficult to select samples associated with specific soil types. As a result of the clustering, the operator has only to associate the soil type with each cluster point and training samples are immediately available for further processing.

It was this latter procedure which was ued in deriving training for the geologic map in the Apollo 9 data. Figure 25 shows the outline of cluster plots from which training was derived. In this case it was only necessary to quickly mark regions containing at least the samples of the classes desired, thus greatly simplifying and speeding the training of the classifier in this case. The specific steps to be followed then are:

1) decide upon the list of classes, and determine the general locality of examples of these classes based on limited ground observation. This information may be from a low altitude aircraft pass, information available from a perhaps out-of-date or inaccurate map or limited ground survey.

2) designate these regions to the clustering algorithm and after clustering identify the specific clusters associated with the classes of interest.

3) From this point the statistics of each class may be computed from appropriate clusters and the classification proceed.

ON THE SPEED AND COST OF DATA PROCESSING

Let us return again to the question of processing speed and economics. Recall it was mentioned earlier that in order to deal with the large volume of data, special care must be exercised in the choice of method such that one of great throughput capability would be possible. It was also pointed out that the aspects of simplicity and processing of a parallel nature contribute in this direction. Perhaps it is now more apparent why the multispectral approach is valuable in this respect. All of the data relevent to a single resolution element on the ground is collected and available for processing at the same instant of time. Thus, rather than requiring the processing of several different images (e.g. from several different spectral bands) one must only process a single vector at a time. The mathematics and algorithms of multivariant analysis are thus immediately available and implementations of this mathematics in parallel processor form are known and well understood. Further, it is possible to carry out ancillary processing steps such as calibration procedures steps such as calibration procedures and data compression schemes[15] immediately at the point of the sensor, thus further compressing the stream and simplifying the type of processing which will be necessary further downstream.*

So far implementations of the classification algorithm used in the above examples have been made on general purpose digital computers, such as was used to generate the above examples, and special purpose analog processors.* Neither of these implementations can be effectively used to judge the cost of computation and throughput rates which could be possible with available technology. It seems clear that special purpose operational implementations would give considerably greater throughput than those now achievable. For example, a few years ago when special purpose digital array processors came on the market, it was indicated that the speed for equivalent processing steps on these special purpose processors step on a general purpose computer. To our knowledge, studies with regard to operational costs of implementing these type of algorithms have not yet been conducted although studies in related fields involving onboard satellite image processing are available.[16]

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* At this point it is not unreasonable to speculate that data compression by an order of magnitude carried out at the sensor will soon be possible without seriously affecting the data quality.

* The SPARC Processor of the Willow Run Laboratories, University of Michigan is an outstanding example of this.

ON THE USE OF SPATIAL INFORMATION

So far we have discussed the use of spectral and temporal variations to derive information from measurements of electromagnetic energy arriving at the sensor. It is also possible to utilize spatial information within the multispectral approach in order to further increase the amount and accuracy of information that can be derived. One such approach to accomplish this is the so-called per field classifier.[17,18,19] In essence, the use of spatial information in this approach results from the fact that points in a near vicinity to one another are likely to be members of the same class. Consider for example, the situation as shown in Figure 19. Here one might be willing to say, "I don't know what all the points in cluster number 4 are, but whatever they are I am willing to say thay they are all members of the same class. What is this class?" Thus, in this case one sees a situation where a set of points rather than an individual point is available for a single classification. In essence then, the mathematics of the situation permits one to use this set of points to estimate the statistical distribution function of the points. This estimated distribution can then be compared with the distribution of each training set to decide upon the proper classification.* Thus, one is comparing a point set to a set of distributions as compared to comparing a single (vector) point to a set of distributions. As may be seen in the reference, a generally higher classification accuracy is achieved by this mode. One does have the preliminary problem though of grouping all points into point sets. This may be either accomplished by a boundary drawing algorithm[14] or through the use of clustering itself as shown in Figure 19.

CONCLUSION

In summary, pattern recognition and the multispectral approach have been described as an analysis procedure which will prove useful in coping with the large quantities of data to be gathered by Earth Resources sensors. This approach was illustrated with two examples, one using airborne scanner data another using multispectral space photography. The manner in which temporal variations in the data can be utilized to increase the quantity and accuracy of information derivable has also been described. Training procedures were identified as an important step in using this pattern recognition approach and the use of clustering to aid in this process was described. Finally, the per field classifier was described as a way in which spatial variations in the data in addition to spectral ones can be used to improve the quantity and accuracy information derivable.

In addition to data volume, remote sensing information systems in the earth resources disciplines

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* The mean and variance of this estimated distribution correspond roughly to tone and texture used by the human photo interpreter.

are characterized by the large number and variety of users of the information to be generated. Many different techniques will be needed working together to supply the information needed by all users. It is our belief that the one described here will ultimately take its place beside the already established ones as a significant technique.

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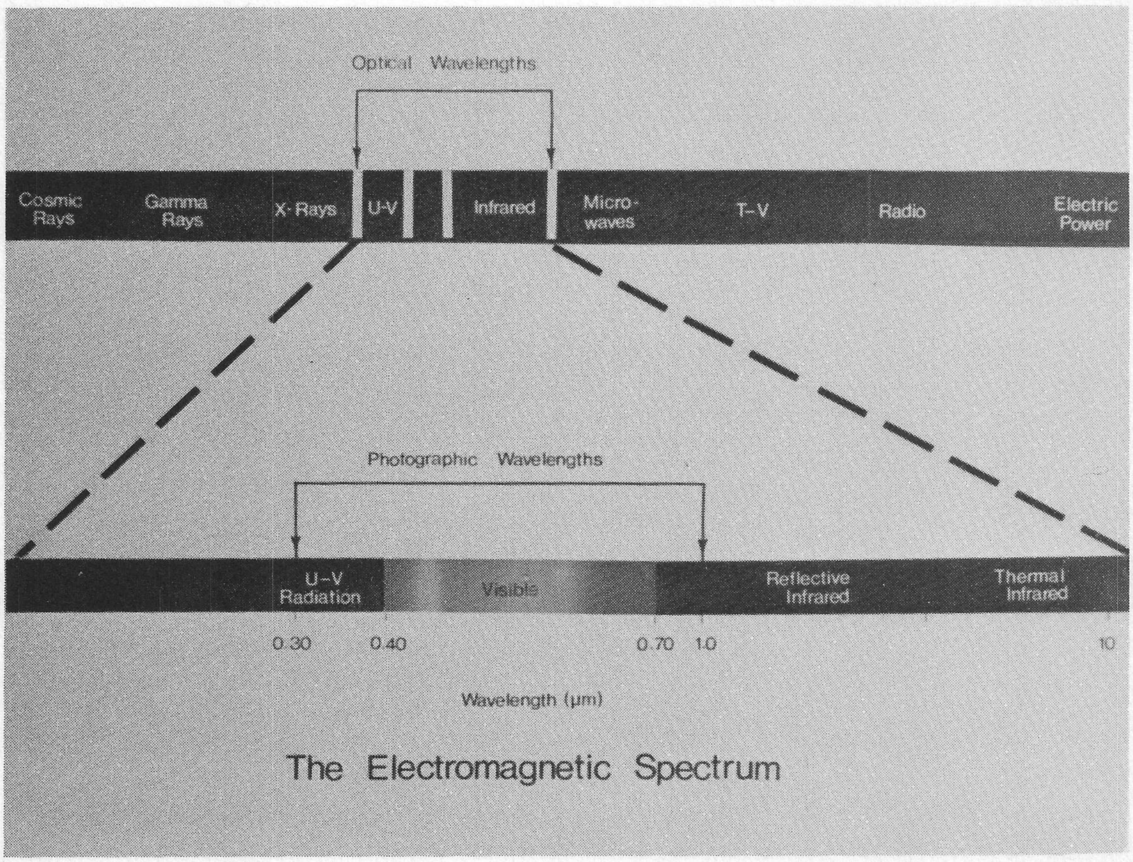

Optical Wavelengths
Cosmic Rays
Gamma Rays
X-Rays
U-V
Infrared
Micro-waves
T-V
Radio
Electric Power
Photographic Wavelengths
U-V Radiation
Visible
Reflective Infrared
Thermal Infrared
0.30
0.40
0.70
1.0
10
Wavelength (μm)
The Electromagnetic Spectrum

Figure 1.

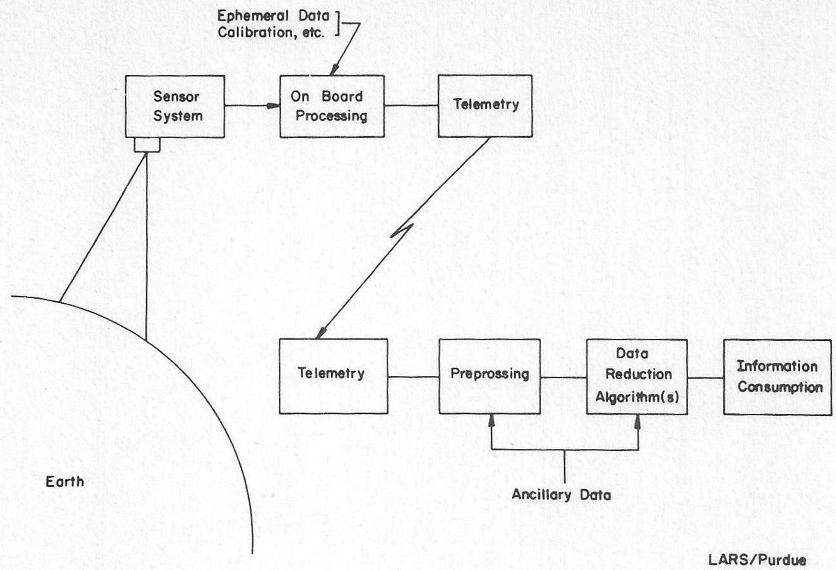


Figure 2. Organization of an Earth Survey System.

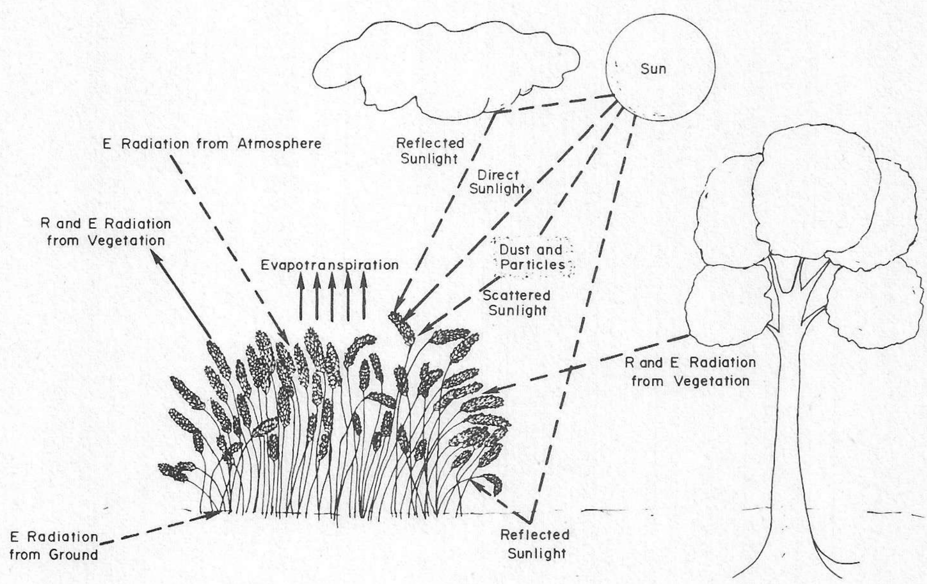


Figure 3. Reflected (R) and Emitted (E) Radiation Energy Exchange in a Natural Environment.

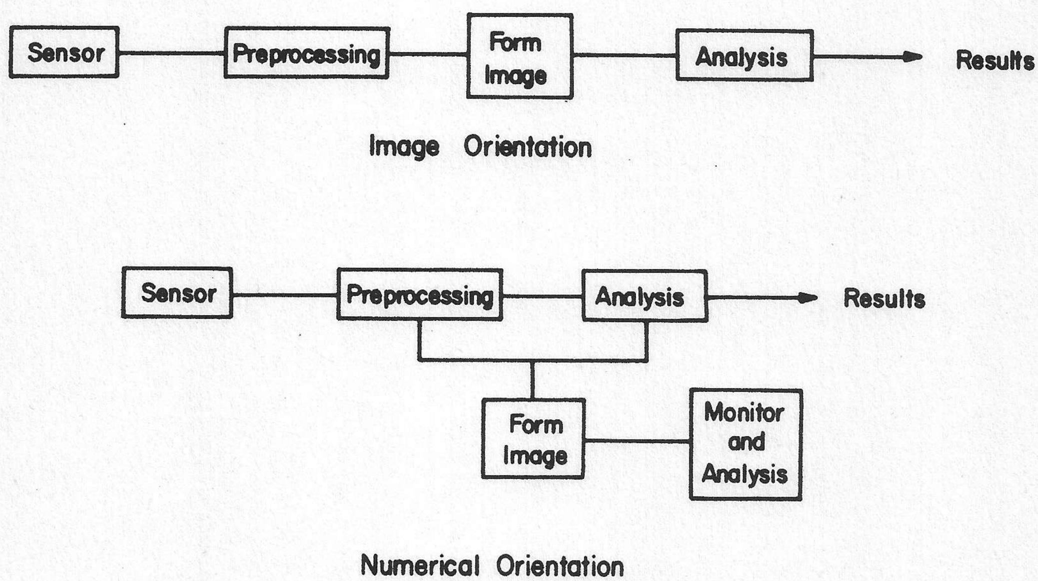


Figure 4. Organization of Image and Numerically Oriented Systems.

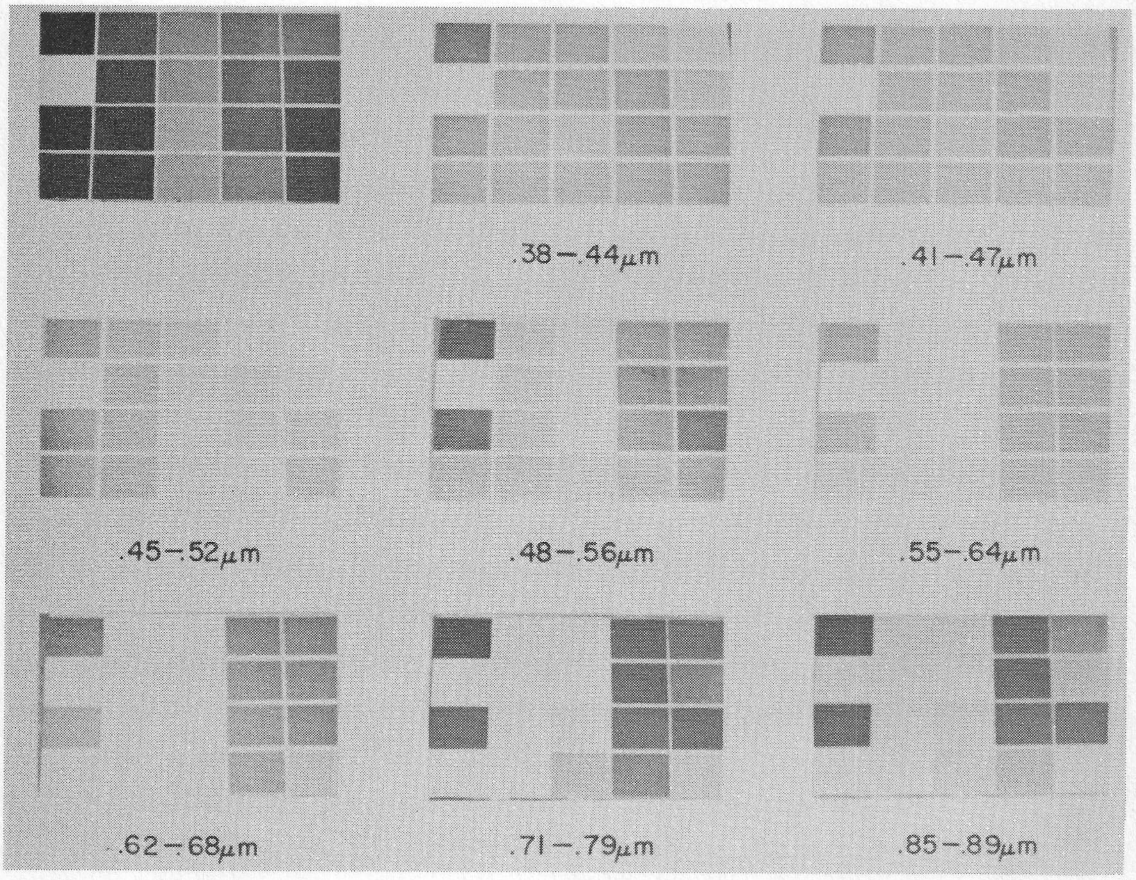


Figure 5. Multispectral Photography of Color Cards.

.4 - .7μm .7 - .9μm 4.5 - 5.5μm (Artist's Concept)

Figure 6. Multispectral Response of Corn, Alfalfa, Stubble, and Bare Soil.

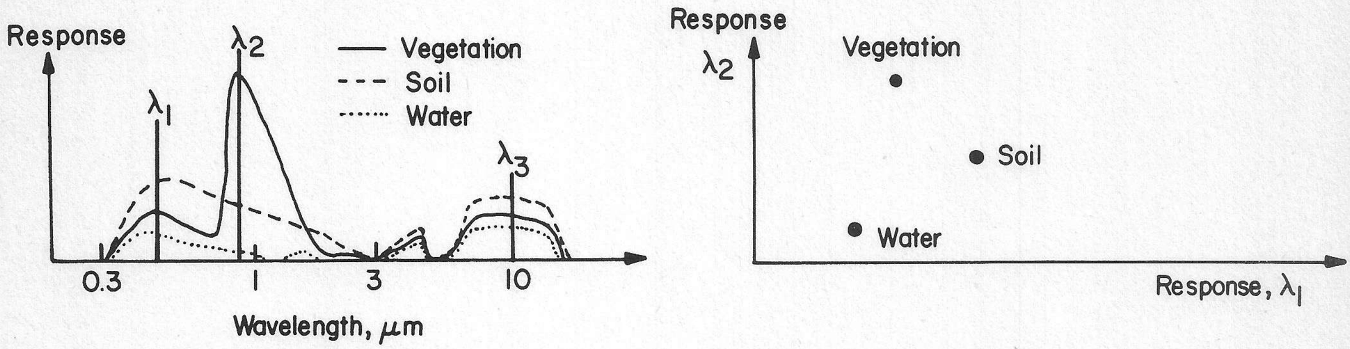


Figure 7. Spectral Data in Two-Dimensional Feature Space.

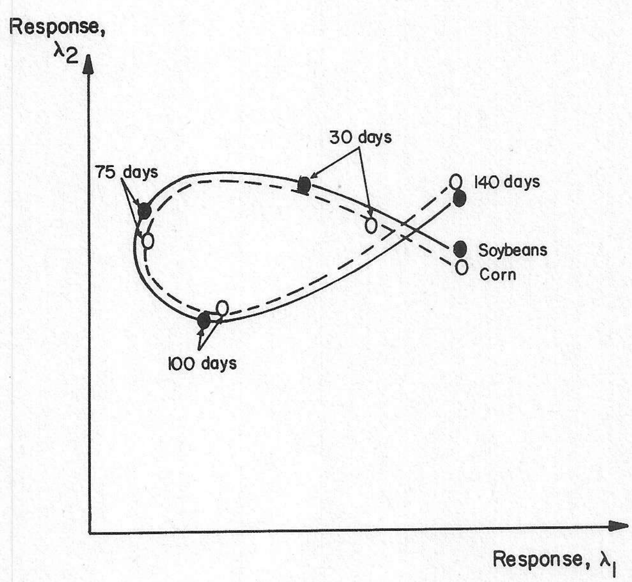


Figure 8. Temporal Change in Two-Dimensional Feature Space.

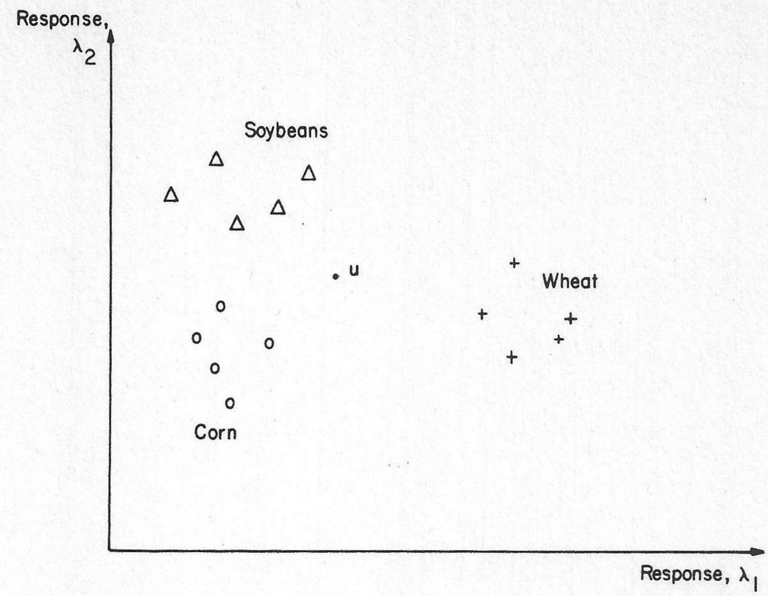


Figure 9. Samples in Two-Dimensional Feature Space.

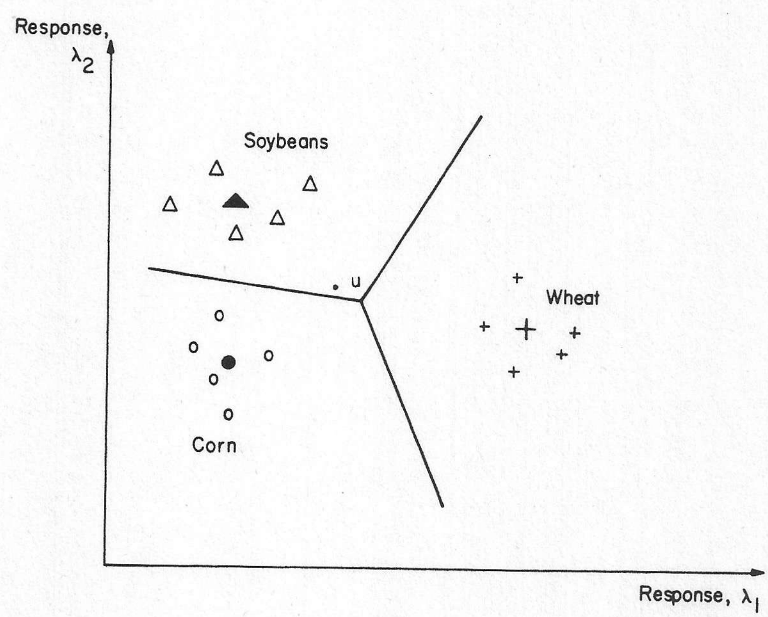


Figure 10. Minimum Distance to Means Classification.

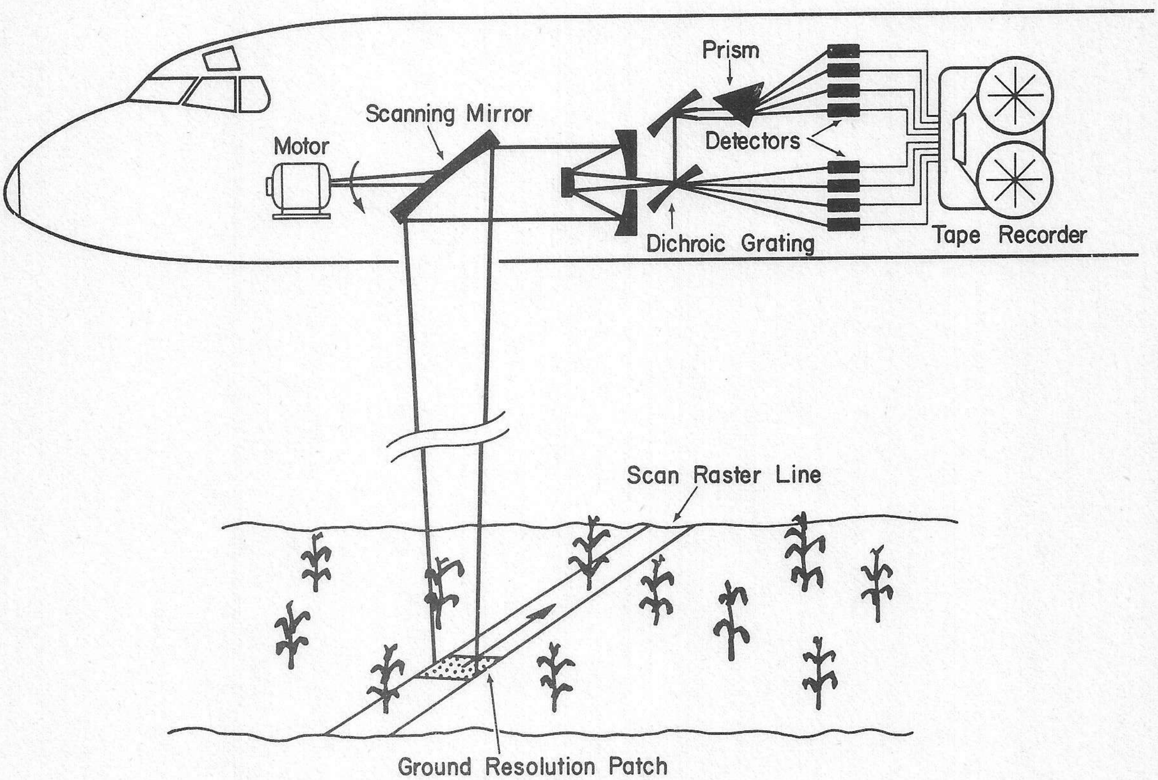
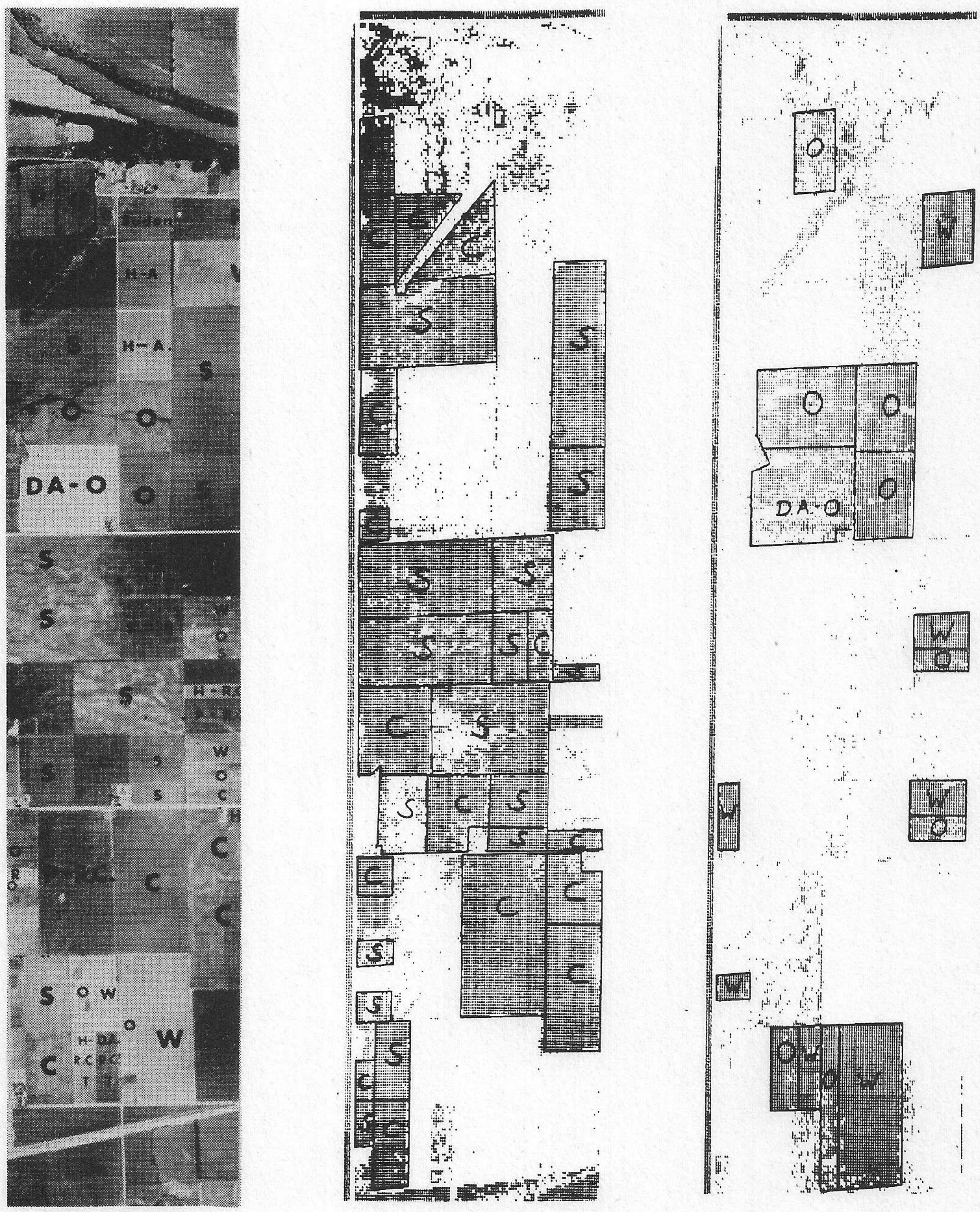


Figure 11. An Airborne Multispectral Scanner.

Air Photo .40-.44µm .52-.55µm .66-.72µm .72-.80µm

Figure 12. Data in Four Wavelengths



Air Photo | Row Crops (Corn & Soybeans) | Cereal Grains (Wheat & Oats)

Figure 13. Spectral Pattern Recognition of Row Crops and Cereal Grains.

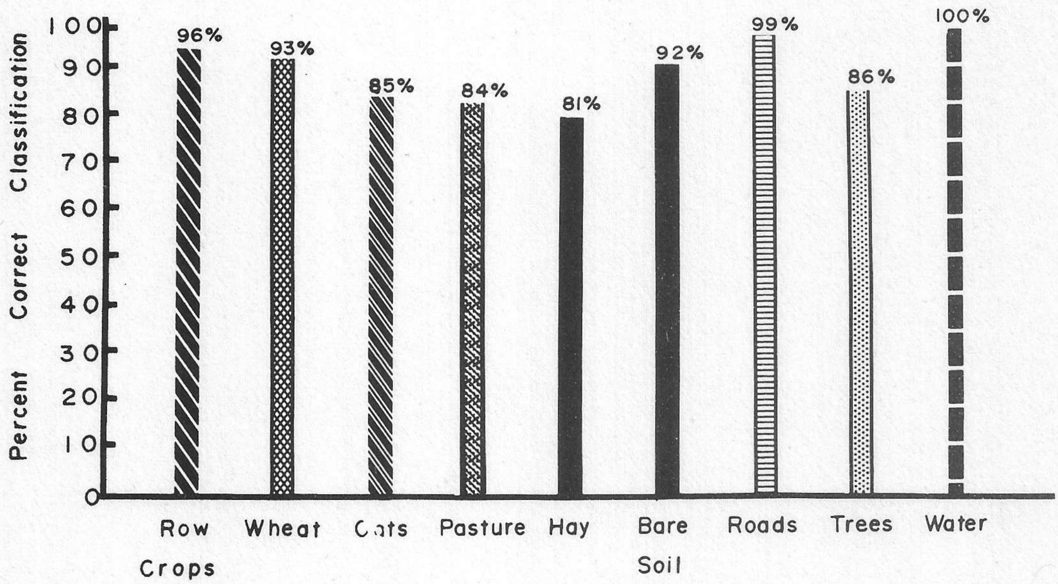


Figure 14. Classification Results for Test Samples.

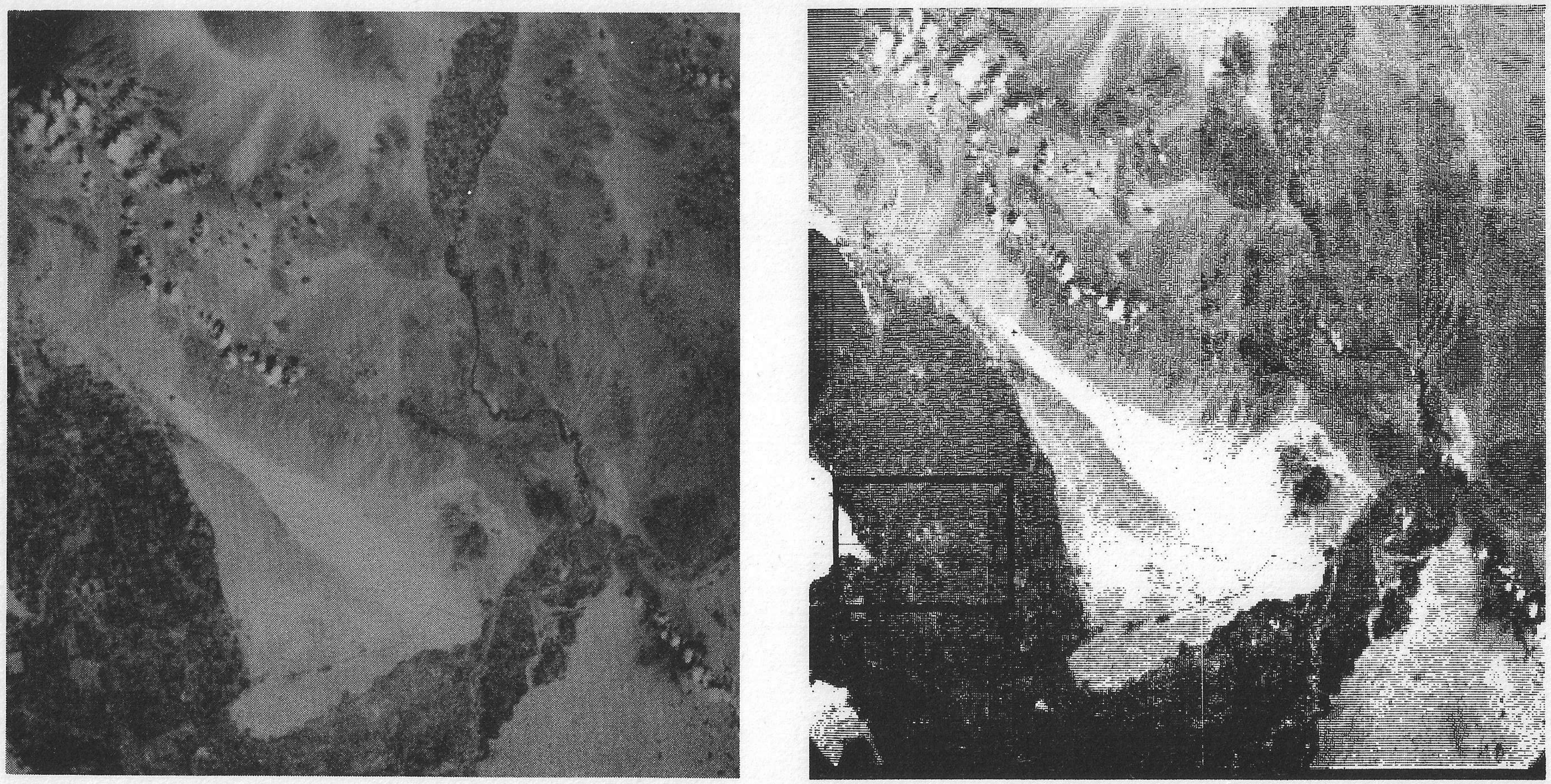


Figure 15. Color Infrared Frame 3698A (Apollo 9) and Gray Scale Panchromatic Computer Printout of the Imperial Valley, California. Visible Green is a Blue Dye; Visible Red is a Green Dye; Infrared is Shown as a Red Dye.

Figure 16. High Resolution Printout of a Section of the Digitized Apollo 9 Frame 3698A, Imperial Valley, California.

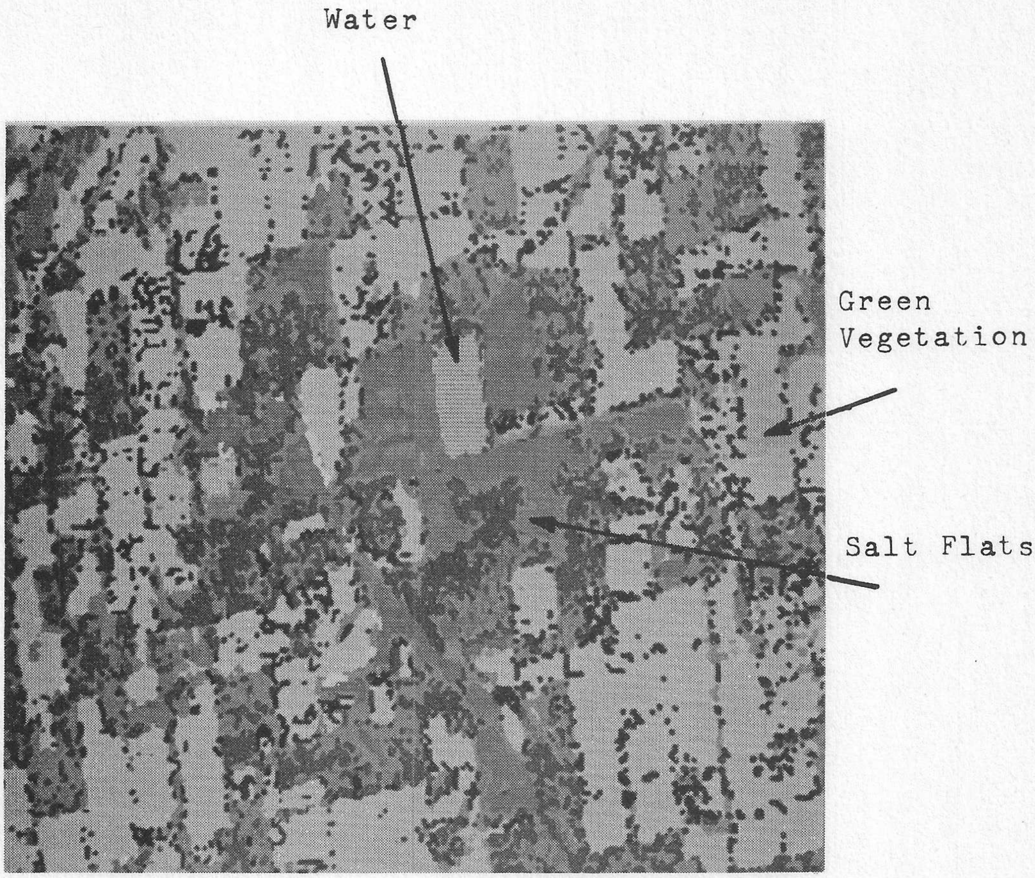
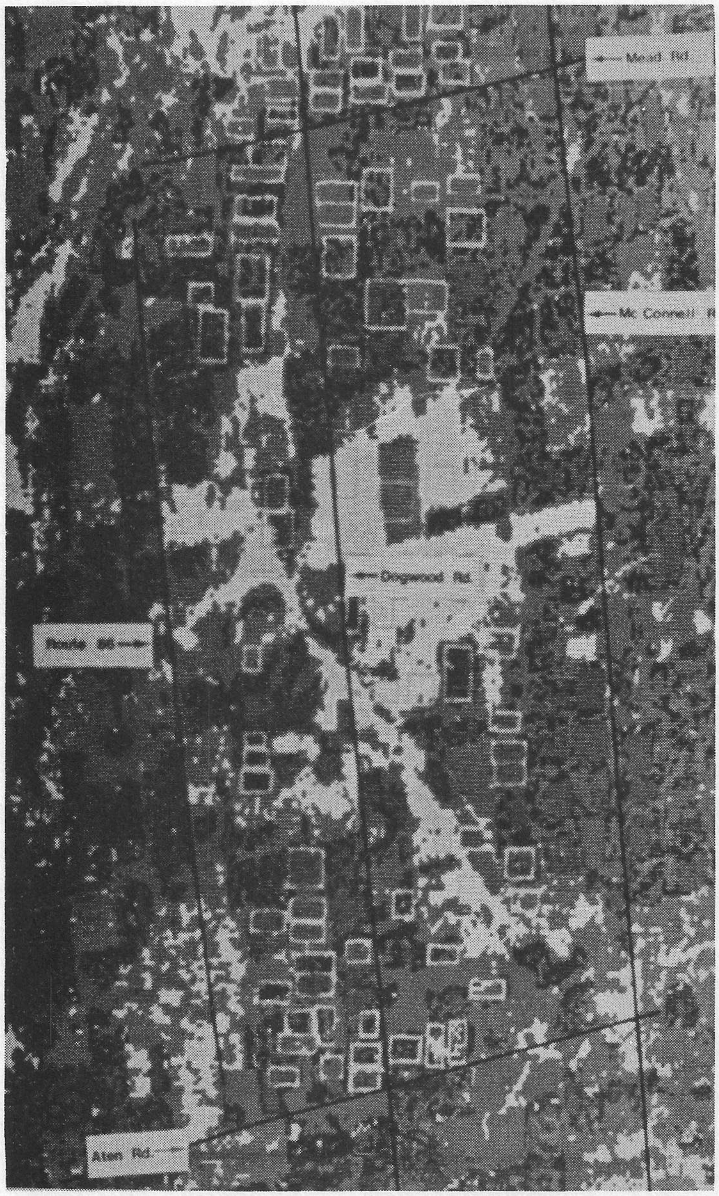


Figure 17. Classification of Apollo 9 Data Into Green Vegetation, Bare Soil, Salt Flats, and Water Classes (Bare Soil is Illustrated by All Other Colors).



Barley	Sugar Beets
Alfalfa	Bare Soil
Water	Salt Flat

Figure 18. Classification Results for Alfalfa, Barley, Sugar Beets, Bare Soil, Salt Flats and Water Classes.

Apollo 9 Computer Map of Imperial Valley Region

Clouds

Cloud Shadow

Basalt

Vegetation

Alluvium

Sand Dunes

Figure 19.

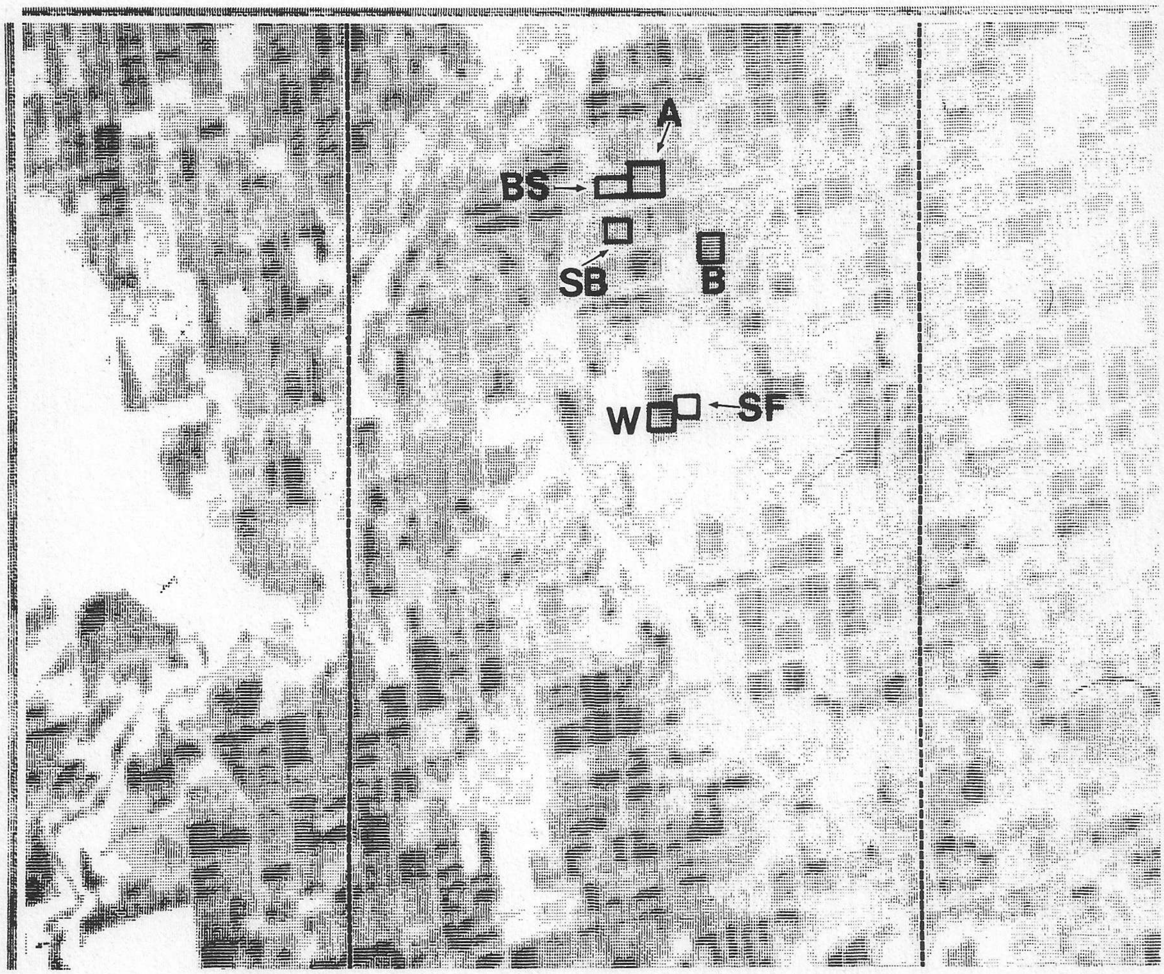


Figure 20. High Resolution Printout with Training Fields.

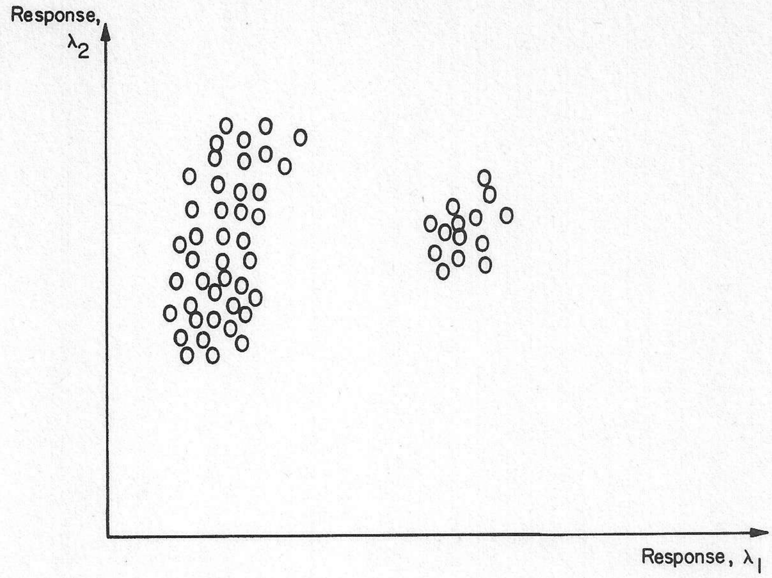


Figure 21. Samples in Two-Dimensional Feature Space.

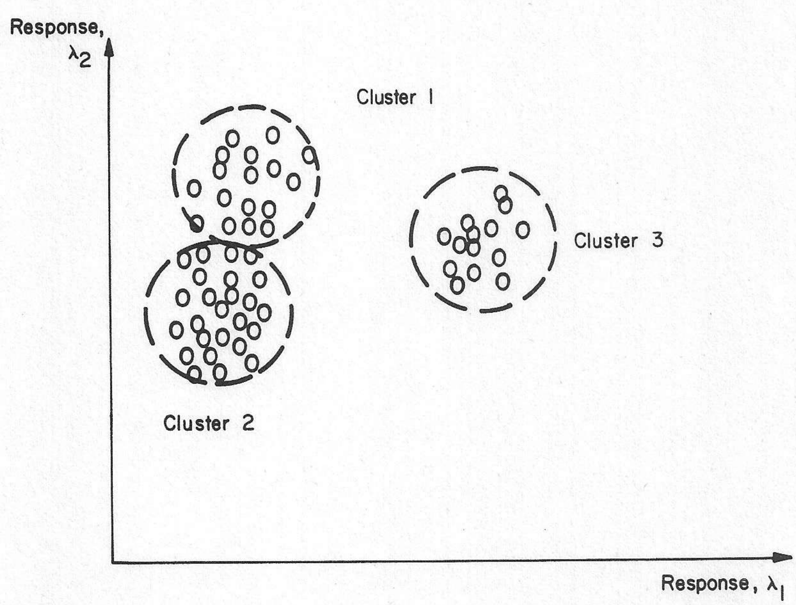
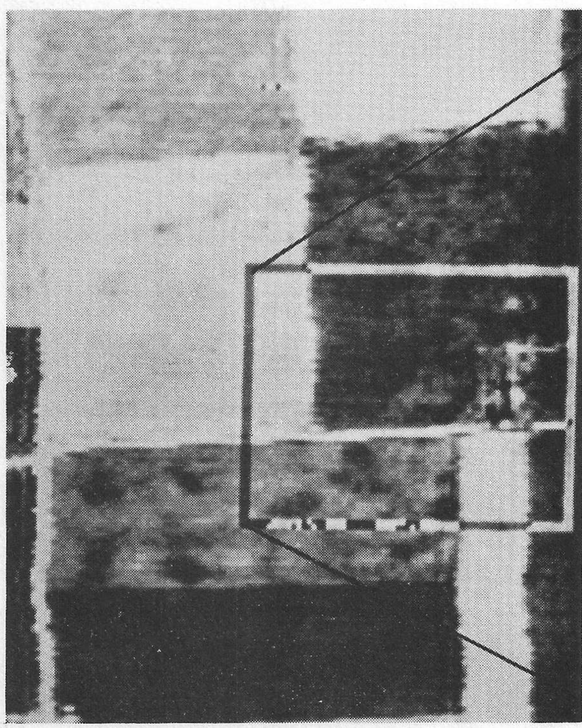


Figure 22. Clustering in Two-Dimensional Feature Space.



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444442111111111111122233555555
444442111111111111111235545555
444442111111111112111255555555
444442111111111122112255545555
444443111111111112223235555555
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Figure 23. Clustered Data Using Four Spectral Bands.

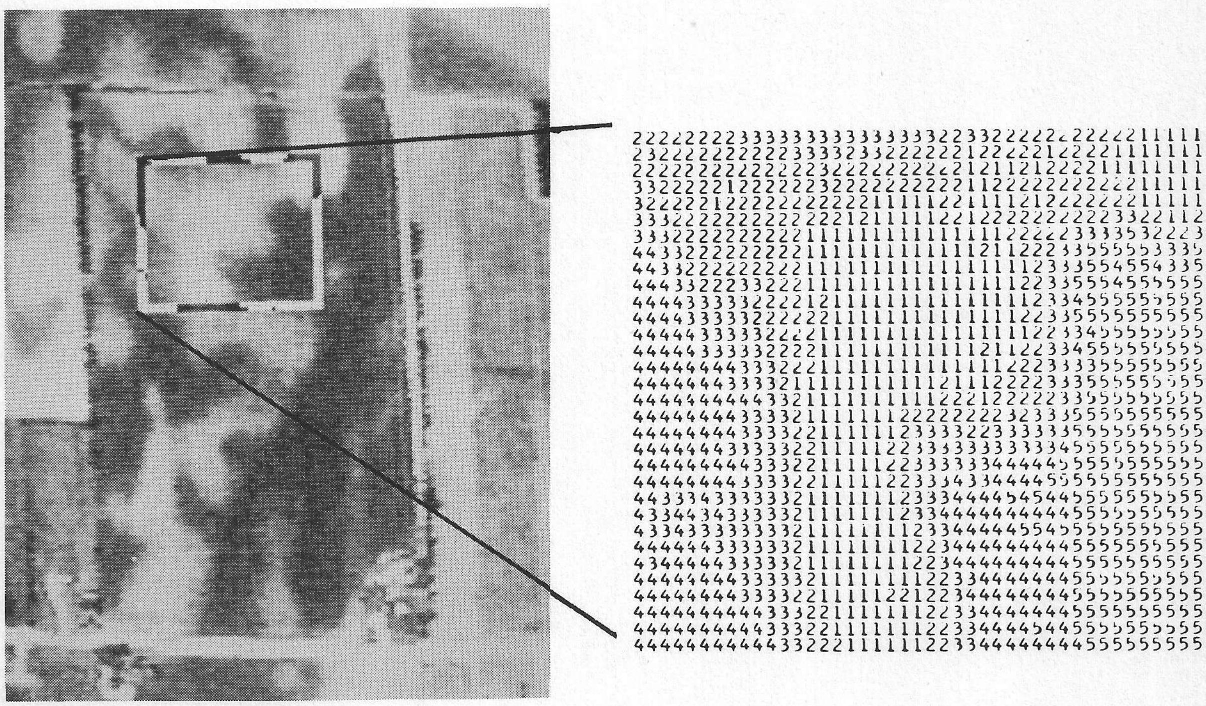

Figure 24. Clustered Data Using Four Spectral Bands.

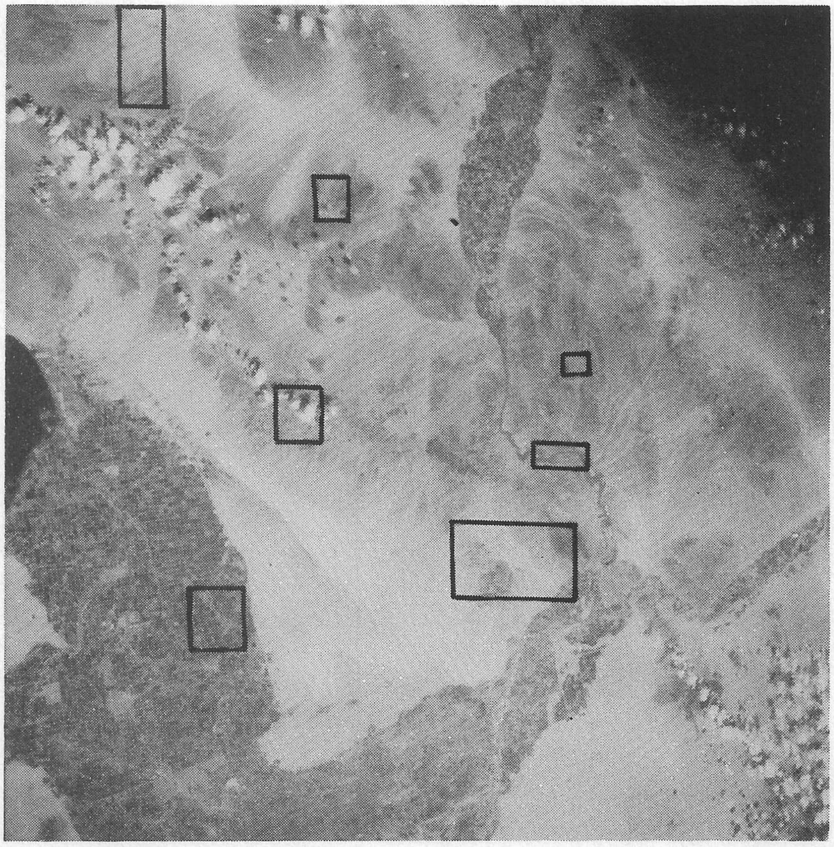

Figure 25. Cluster Fields for Machine Aided Training.