Machine Processing for
Remotely Acquired Data

by
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PREFACE

This paper presents a general discussion intended to introduce the prospective user to multivariate data analysis techniques as applied to the processing of remotely acquired earth observational data. Not only are numerically-oriented remote sensing systems discussed, but attention is given to image-oriented systems, the other main branch of remote sensing, in order to establish the relationship between the two.

ABSTRACT

This paper is a general discussion of earth resources information systems which utilize airborne and spaceborne sensors. It points out that information may be derived by sensing and analyzing the spectral, spatial and temporal variations of electromagnetic fields emanating 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 and 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 aircraft and the Earth Resources Technology Satellite (ERTS-1). Both manual and machine-aided training techniques for the pattern recognition algorithm are described. Other data processing activities are also mentioned.

Section I: INTRODUCTION: <u>WHAT IS REMOTE SENSING?</u>
<u>HOW IS INFORMATION CONVEYED?</u>

Imagine that you are high above the surface of the earth looking down. 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 might the system to extract it look like?

Remote sensing provides some answers. Remote sensing is the science and art of acquiring information about material objects from measurements made at a distance, without physical contact with them. In remote sensing, information may be transmitted to the observer either through force fields or electromagnetic fields, and 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 these variations and
. Relate these measurements to those of known
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 measure-
ments analyzed to determine which points on the earth
contain water and which do not.

This paper concerns electromagnetic fields, which
appear to have a greater potential than force fields.
Figure 1 reviews the spectrum of electromagnetic fields.
The visible portion, extending from 0.4 to 0.7 micro-
meters, 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 micro-
meters 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
reflected from it.

In addition to the optical wavelengths, pre-
liminary results using passive microwave and radar
sensors indicate considerable promise for this micro-
wave portion of the spectrum. For reasons of sim-
plicity 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 data and data de-
lineating 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 in the case of the Earth Resources Technology Satellite, or through direct package return, as used with SKYLAB. There usually then is a need for certain preprocessing of the data before the final processing with one or more 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 the many potential consumers of this information are not accustomed to receiving it from a space system and may indeed know very little about its information-providing capabilities.

It is necessary to thoroughly understand the portion of the system preceeding the sensor, particularly the energy exchange in a natural environment (Figure 3). It is possible, of course, to detect the presence of vegetation by measuring its reflected and emitted radiation. One must understand, however, that many experimental variables are active. For example, the sun provides a relatively 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 earth's surface and the point of observation. Even more important is the variation in the vegetation itself. It is possible to deal with these experimental variables in several ways. These will be discussed later.

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 measurements 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 TWO MAJOR BRANCHES OF REMOTE SENSING

When we consider remote sensing today, the field
has two major stems originating from two different
technologies. These two types of systems will be re-
ferred 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 photo-interpreter.
Photographic film is used to measure the spatial
variations of the electromagnetic fields, and the
photo-interpreter relates these variations to specific
classes of surface cover. Numerically oriented sys-
tems, on the other hand, tend to involve computers
for data analysis. Although the photo-interpreter
and the computer, respectively, tend to be the identify-
ing components in each type of system, it is an over-
simplification to say that they are uniquely related
to them. This becomes clearer upon further examination.

Comparing the two systems (Figure 4), both types
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-orient-
ed type, it is a step in the data stream and must pre-
cede the analysis. Numerically oriented systems, on
the other hand, need not necessarily form an image.
If they do, and in earth resources work they usually
do, it may be at the side of the data stream, as
shown. Images may be used to monitor the system and
perhaps to do some special analysis. An image is,
of course, the most efficient way to convey a large
amount of information to a human operator. Thus,
both types of systems, use images but the use is
different in the two cases.

Section III: SENSOR TYPES AS RELATED TO SYSTEM TYPES

In considering the design of information gather-
ing systems, it is important that the type of sensor
as well as the means of analysis are well-mated to
the type of system orientation. Thus, let us brief-
ly consider the types of imaging spaceborne sensors
available.

Perhaps the single most distinguishing character-
istic of earth resources information systems is that
a very large amount of data can be, and, indeed, must
be, gathered in order to derive 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 on the next page is a
categorization of imaging sensors into three broad
classes: Photographic, television, and scanner. The
table also provides example advantages and disadvan-
tages of each.

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

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 carry-
ing along a large quantity of the storage media
(photographic film for the photography case) when us-
ing a television sensor. One may view this either as
an advantage of size and weight or as one of efficiency
in that a satellite may be operated a very long time
with a single servicing. Television sensors are re-
stricted 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 long been in use, as have appropriate analysis techniques. This type of system also has the advantage of being easily acceptable to the layman or neophyte, an advantage important in the earth resources field, with its many new data users. Similarly, it is well-suited for producing subjective information and is especially suited to circumstances where the classes to be identified in analysis cannot be precisely selected 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 to the layman. This type of system is best suited for producing objective information, and surveys covering large areas are certainly possible. Numerically oriented systems tend to be generally more complex, however.

In summary, the state of-the-art is that there are two general branches of remote sensing; this duality exists primarily for historical reasons and because these technologies began at different points.

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.

Numerically oriented systems and a particular
type of data analysis useful for them will now be
examined.

Section IV: THE MULTISPECTRAL APPROACH AND PATTERN
            RECOGNITION

How does one begin the task of devising a tech-
nique for analyzing large quantities of remotely
sensed earth observational data? Certainly one
must make optimum use not only of man's ability but
also of modern computer devices. This consideration
strongly influenced the route that the technology
has taken. Though much basic research effort has
been expended, few practical methods have been un-
earthed for the machine analysis of data as complex
as earth observational imagery based upon the spatial
variations in the scene. Thus, if much of the routine
and repetitive aspects of the analysis are to be
successfully turned over to a machine so that low-cost,
high-throughput analysis is obtained, a fundamentally
simpler approach must be taken. Basing the analysis
primarily on temporal variations in the scene held
reason for concern in early work also, since, in
this case, no information could be derived based
solely on observations taken at a single point in
time.

Fortunately, the third of the three, spectral
variations, did appear to hold promise for machine
analysis based upon feasibility studies into what has
come to be called the multispectral approach. The
route taken by the numerical branch of remote sensing
has been to utilize spectral variations as fundamental
to the analysis later adding to the processing the
use of spatial and temporal information as circumstances
require and permit.

An initial understanding of what is meant by the
term "multispectral approach" may be obtained by con-
sidering 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, indi-
cating a high response or a large amount of red light
energy being reflected. 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[2]. Note that in the
three bands alfalfa has responses which are dark, light,
and dark, respectively, whereas bare soil is gray, dark
and 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 in which a very quantitative measure
of the color of a material is used to identify it.
Color, however, is a term usually limited to the re-
sponse of the human eye; the precise terminology of
spectroscopy is more useful in understanding the
multispectral approach, and 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 left 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 wave-
lengths 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 re-
spect to one another. For example, in the left soil
has the largest response at wavelength λ_1; this mani-
fests itself in the right plot in the fact that soil
has the largest abscissa value (the greatest displace-
ment 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

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*This space is referred to as feature space.

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 he 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 temporal nor spatial information has
been involved, only spectral. Temporal information
can be utilized in several ways. Time is always a para-
meter of the spectral response of surface materials.
As an example, consider the problem of discriminating
between soybeans and corn, and refer to Figure 8. 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 species with time as a parameter. Upon
planting and for some period thereafter, fields of soy-
beans and corn would merely appear to be bare
soil from an observation platform above them. Event-
ually 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 vege-
tation 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 geometries 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 them-
selves. 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). 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-day and 100-day points. In this case the separ-
ation of the two materials is relatively slight.

However, if this data is replotted in four-dimensional space, response at λ_1 and λ_2 and 75 days as dimensions one and two and λ_1 and λ_2 at 100 days as dimensions three and four, the small separabilities 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 histori- cal record of the changes taking place in a scene as a function of time.

Let us 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 soy- beans 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. Moreover, response variation within a class may be expected of any earth-surface cover. The extent of response differences of this type cer- tainly 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 abounds with algorithms or procedures by which this can be done.[5,6] In order to illustrate the concept, 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.

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

In very simple situations where data from the various classes are quite well separated in this feature space, an even simpler technique, called "level-slicing", can be used. The term level-slicing came into use when analysts of black and white photography began identifying (Figure 6) certain materials from others in a scene by their range of gray levels. Thus, by identifying the areas on the film which had this range or slice of levels, one could locate all of the regions containing that material.

This simple concept immediately extends to the multiband case where one looks for areas in which the data falls in one range in the first band, a second range in band two, and so on. From the feature space viewpoint this method identifies data points which fall in a horizontally or vertically oriented rectangle.

For many analysis problems of practical interest, a somewhat more sophisticated procedure allowing for more generality in the location and form of the decision boundaries is called for. One such algorithm, the so called Gaussian Maximum Likelihood Classifier, has been especially well-studied for this purpose. In this case the initial samples of each class are used to estimate not only the mean value for each class, but also its covariance matrix. This latter matrix shows not only the variance present in data from each spectral band but also the degree of correlation between bands. Under the assumption that the data from each class have a Gaussian (or bell-shaped) distribution, these mean values and covariance matrix completely define the class distribution and for the two spectral band case they might appear as shown in Figure 11 (a). A given data point is then assigned to a class according to which class Gaussian density function has the largest value (or maximum likelihood) for that response value in λ_1 & λ_2. Thus, the decision boundaries occur at the intersection of class density function as shown in Figure 11 (b) and, are in general segments of second order curves, i.e. parabolas, hyperbolas, ellipses, and circles with straight lines as a degenerate case.

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

Section V: THE MULTISPECTRAL SCANNER AS A DATA SOURCE

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 as a multi-spectral scanner. Figure 12 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. Gratings 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, deter-mined the response as a function of wave-length 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.

Section VI: AN ILLUSTRATIVE EXAMPLE

As an example of the use of this type of sensor and analysis procedure, results 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

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

agricultural significance. Four-dimensional data (four spectral bands) were used and the classification scheme was Gaussian maximum likelihood discrimination.[4] The data are shown in Figure 13 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, A - alfalfa, T - timothy, RC - red clover, R - rye, SUDAN - sudan grass, P - pasture, DA - diverted acres, and H - hay.

Figure 14 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 quantitative 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 15. It is seen that all results for all classes are above 80% correct.

The same procedures using both aircraft and satellite 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 VII: **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.

Two conditions that a class must meet to be useful are to be separable from all others and to 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 analyzed. On
the other hand, if no one is interested in locating
iron ore deposits within the region, there is no
reason to define such a class. It shall be seen pre-
sently that one may name classes of informational
value and then check their separability, or vice versa.

A second matter is determining when a class
actually becomes defined. In an agricultural survey,
for example, simply naming a class soybeans does not
define it precisely enough. For instance, 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 pre-
cisely 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 suffi-
ciently 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 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 be-
comes 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 im-
portant. There are two approaches to obtaining train-
ing 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 there-
after 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 considerable 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 tha analysis can proceed. In the case of populated or accessible areas, this knowledge usually comes from ground observations. In the case of inaccessible and/or populated ones, it could perhaps also come from a very limited, low-altitude aircraft mission or by direct manual interpretation of imagery. 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 further an example follows in which a pattern recognition scheme was trained and then used to classify a relatively larger amount of data. Data for this experiment was collected by the multispectral scanner system

(MSS) of the Earth Resources Technology Satellite, ERTS-1. From its orbital altitude of approximately 9000 kilometers (560 miles) this sensor has an instantaneous field of view of approximately 80 meters on the ground. The all-digital system transmits data to the ground in frames of imagery covering a square area 185 kilometers (100 nautical miles) on a side. The data presented in image form would result in an image made up of 2300 scanlines with 3350 samples per scanline. The sensor provides spatially registered data in four spectral bands from .5 to 1.5 micrometers. Thus, a single data set (frame) consists of approximately 7.5 million four-dimensional points.

Though by the previous illustration it is apparent that pattern recognition techniques can be used effectively on data gathered from an airborne system, they are even more ideally suited to satellite-gathered data where it is possible to gather a very large amount of data in a very short time, thus holding significant and important experimental variables constant during the data gathering activity. Said another way, given that a specific problem requires the gathering of a large amount of data, pattern recognition techniques which function efficiently and cost-effectively only on very large quantities of data are ideally suited for the analysis test from the standpoint of data throughput.

The particular frame of data used for this example is the first frame gathered by the ERTS-1 satellite MSS system after its launch (Frame ID 1002-16312). It was gathered on July 25, 1972 and is of the Red River Valley areas of Texas and Oklahoma. The frame is centered on a point 15 miles southeast of Durant, Oklahoma and approximately five miles north of the Red River. A simulated color infrared photograph made from the frame is shown in Figure 16.

A maximum likelihood Gaussian classification scheme was trained using seventeen classes from this data set. The data were then classified into these seventeen spectral classes. Figure 17 shows a display of the classification results in image form. The detailed analysis results themselves, that is, the identifying class number associated with each point plus the likelihood value for it, are stored on magnetic tape. Figure 17 presents these quantitative results in a form suitable for qualitative evaluation. This figure was constructed by associating each class or group of classes with an individual color. It is noted in passing that as such, then, Figure 17 cannot accurately be called an enhanced image. More

properly it is a means of displaying a large volume
of quantitative results in qualitative image form.

The seventeen classes are presented here in
eleven colors. This grouping was done because it is
not possible for the human eye to discriminate bet-
ween many more than about ten or eleven colors. The
colors and their corresponding estimated cover types
are listed as follows:

Category	Spectral Class	Color Code	Cover Type
1	2,3,4,5,6 7,8,12,13	Yellow, Tan, Light Green, Brown	Various classes of Range lands and pastures
2	1,17	White, Light Gray	Sandy or Bare Soils, Light Vegetation, Agricultural fields with sparse canopy
3	9,10	Dark Green	Forests and woodlots
4	14,15,16	Dark Blue, Blue Gray, Aqua	Water (3 subclasses)
5	11	Dark Purple	Atoka Reservoir

There remains then the problem in this experi-
mental situation of establishing the adequacy of
the accuracy to which the classification algorithm is
functioning. In this case, that was done through
low-altitude air photographs and a ground observation
mission carried out five days after the satellite pass.
For example, Figure 18 shows an even more detailed
classification of a region in the vicinity of Lake
Texoma in the west central portion of the frame. This
classification was done using eighteen spectral classes
in four broad land use groups. The color code used
in this Figure is as follows:

Category	Spectral Class	Color Code	Cover Type
1	12,13,16 17,18	Lt. Blue, Dark Blue, Blue Gray, Med. Blue	Water (5 classes)

Category	Spectral Class	Color Code	Cover Type
2	1	White	Sandy and Light bare soil, light colored dry vegetation, agricultural fields with low crop coverage
3	7,14	Red	Agricultural fields with high coverage
4	2,3,4,5, 6,15	Yellow, Light Brown, Light Tan	Pasture, Range land
5	8,9	Light Green	Forest, Sparse canopy
6	10,11	Dark Green	Forest, more dense canopy

Figure 19 shows an enlargement of the west end of Lake Texoma. The Red River is seen winding through a forested area beginning in the southwest corner of the frame and entering Lake Texoma near the western-most end. A delta has been formed at the point of entry and has been classified into the class indicated by white (sandy and light bare soil). Subcategories of water indicated on the color coded classification results in various shades of blue are also apparent. There is a small inlet on the north shore directly north of the delta. Figure 20 shows an oblique low-altitude air photo taken from a point just north of this inlet looking south. The delta and the gradations in water turbidity are apparent in the air photo.

Notice also that though the instantaneous field of view of the multispectral scanner is approximately 80 meters, a bridge crossing Lake Texoma near the southwest corner of Figure 19 was correctly classified based on the classes available to the pattern recognition algorithm. This bridge is an ordinary two-lane bridge.

A study of a number of low-altitude photographs in comparison with the color-coded classification results suggests that the broad land use categories shown in Figures 17, 18, and 19 are indeed well-classified. If true, one has a capability for deriving a land use map of a region almost immediately. Viewing Figure 17 one could quickly draw boundaries between areas which are

used for various types of agricultural land, range
land, forest and other land uses. In addition, the
intrinsically quantitative nature of the approach
allows one immediately to estimate acreages in each
land use by counting sample points classed into each
of the classes.

A more complete discussion of the analysis of
this frame is available in the literature.[8] Other
demonstrations of the use of satellite imagery[9,10]
already have established the accuracy possible with
machine analysis for land use mapping purposes;
future work will no doubt corroborate this conclusion.
We will concentrate here therefore on the procedures
and computational algorithms necessary to achieve
these results.

At present the use of various classification
algorithms for this purpose is fairly well understood;
however, the training of an algorithm is still a
time-consuming process requiring a trained and sophis-
ticated analyst. Earlier it was pointed out that the
chosen classes must satisfy two criteria to be valid.
They must be separable, a restriction imposed by
the reflectance properties of the scene, and they
must be of informational value, a restriction imposed
by the intended use of the analysis results. Both
of these criteria must be simultaneously satisfied.

Furthermore, as was previously pointed out, the
classes are not really defined until the training
data or statistics describing them exist. The diffi-
culty of determining eighteen sets of four-dimensional
mean vectors and co-variance matrices can be readily
envisioned, particularly if it were necessary to
identify the sample points used to estimate these
statistics manually. Over the last few years research
has been directed toward machine-aided methods for
this process. One such procedure involves the use of
a type of classifier not utilizing training samples.
It is referred to as an unsupervised classifier.
Assume, for example, that one has some two-dimensional
data (as shown in Figure 21); assume also that one
knows there are three classes of material in this
data but the correct association of the individual
points with the three classes is unknown. The approach
is to assume initially that the three classes are
separable and check this hypothesis subsequently.

There are algorithms (computational procedures)
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 results of applying such a procedure[14] might be as shown in Figure 22. There remains, then, the matter of checking to be sure that the points assigned to a single cluster all belong to the same class of material. That is, the method automatically establishes classes which are separable but not necessarily ones which are of informational value. Thus, in comparing supervised versus nonsupervised classifiers, it is accurate to say that in the supervised case one names classes of informational value and then checks to see if these classes are separable while in the nonsupervised case the reverse is true.

Figure 23 shows the result of applying such a clustering technique to some multispectral data. The algorithm was instructed to form five clusters. A 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 useful to speed the training phase of the classifier by aiding the human operator in obtaining points grouped according to the class that they originate from. The statistics of each cluster point can be immediately computed from the cluster results so that decision boundaries are quickly established. The operator is thus relieved of the necessity of locating and separating individual resolution points of fields for training each class.

The value of such a procedure is even greater in cases where large groups of points associated with the same class and located contiguous to one another are not present as they were in Figure 23. 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.

Such clustering techniques are very useful in the training phase of utilization of a supervised classifier. The specific steps to be followed in training a classifier are dependent not only upon the data set but also upon the users informational needs. The following steps, which are similar to the ones used in the ERTS data analysis example, are rather typical:

1. Make available to the clustering algorithm every mth sample of every nth scanline. It is ordinarily not necessary to cluster every point and indeed to do so unnecessarily wastes computer resources. The values of m and n needed in each situation are a matter of judgement depending on the availability of computing resources and how the classes distribute themselves over the data set to be analyzed.

2. Examine the results of the clustering to establish first that each of the clusters is sufficiently separable from the others and second that the clusters are associated with some class of material of interest.

3. Manually select additional training sets as may be needed to treat special situations.

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

Section VIII: ON THE SPEED AND COST OF DATA PROCESSING

Let us return to the question of processing speed and economics. 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.

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.* Some work has begun in

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*The SPARC Processor of the Environmental Research Institute of Michigan is an outstanding example of this.

looking at operational implementations of the processing
algorithms which have been studied under research circum-
stances. Both software techniques, such as "table look-up"
implementations of classifiers,[15] and advanced hardware
techniques[16,17] could produce operational processing cost
reductions of several orders of magnitude over those
processing costs of general purpose digital computers
and the highly flexible software necessary in the research
environment. Results on quantitative comparisons between
processing approaches[18] and their costs are not yet abundant.

Section IX: ON THE USE OF SPATIAL INFORMATION

So far we have discussed the use of spectral and
temporal variations to derive information from measure-
ments 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.[19,20,21] 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 23. 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
that 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 avail-
able 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 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,[20] 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 it-
self as shown in Figure 23.

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

Section X: DATA PREPROCESSING STEPS

Having now treated the portion of the system involv-
ing data analysis (see Figure 2) it is appropriate that
we return briefly to the preprocessing section of the
system. Depending upon the type of information needed
and therefore the type of analysis to be used, there are
a large number of possible data preparation or preprocess-
ing steps which prove necessary of helpful. The table
given below enumerates some of them.

CALIBRATION

. Radiometric (intensity) Manipulation
. Geometric Manipulation

ENHANCEMENT

. Spatial Frequency Operations
. Multivariate Transformations
. Convolutional Filtering

MULTI-IMAGE OPERATIONS

. Inter-image Addition Subtraction, etc.
. Inter-image Registration

DATA PRESENTATION

Generally, on board the sensor platform, as was
previously mentioned, various types of calibration
information are derived.   Thus, a possible preprocess-
ing step is to apply this calibration information to the
data. This may take the form of radiometric calibration
in which corrections are made for variations in the at-
mospheric transmission, system gain, sensor aging and
the like. A second type of calibration is that associated
with the geometry of the image. Usually it is necessary
to make intra-image corrections of both a relative and
an absolute type. For example, in the ERTS-1 MSS images
a type of skew distortion arises because the earth is
rotating beneath the satellite during the period of time
that a single frame is being sensed. Thus, a correction
must be applied on an intra-image basis in order that
individual resolution elements will have the proper
relative location with respect to one another.

On the other hand, it may be necessary for storage
and retrieval purposes to establish the location of each
resolution element relative to an earth-oriented coordinate

system on a more absolute basis. An example of such an
operation is the so-called scene correction or precision
image processing done with the ERTS-1 imagery.

Another example of a calibration type of preprocess-
ing is the so-called angle correction process. The
amount of radiation which is reflected from a given
scene area is dependent upon both the angle from which it
is illuminated and the angle from which it is viewed.[22]
This problem has been long known to the field of photo-
interpretation in terms of the so-called image "hot spot".
It is possible to process the data in such a way that
the hot spot appears to have disappeared. Unfortunately,
since the angle affect depends not only upon the illumination
angle and view angle but also upon the scene material on
the ground, it is generally not possible to process
the data to a point of being radiometrically correct. In
short a suitable approach to this problem from a radiometric
standpoint is not known at this time.

In recent years a considerable amount of work has been
done in the image enhancement area. Spatial frequency
operations have been widely studied for such purposes as[23]
enhancing boundaries in the imagery, removing low-frequency
shading affects, correcting for distortions introduced by
the data transmission system, removing single frequency
coherent noise and the like. Enhancement by carrying out
a multivariant transformation on multispectral imagery
for enhancement purposes has also been examined.

Multi-image operations are also some times necessary
and desirable. One of the most important multi-image
operations is that of achieving registration between
two images collected over the same scene at different
times or in different portions of the electromagnetic
spectrum. This problem has great importance and it has
been extensively studied. Techniques today tend to fall
into two broad classes. The first is those involving
primarily optical techniques developed primarily in the
field of photogrammetry using image projection techniques
and ancillary data derived from system characteristics
and operation. The second approach to the problem
differs from this in that registration is achieved
generally through point by point processing and utilizing
information derived from the data itself. Two-dimensional
image correlation is a common approach in this latter
case.[24,25,26]

Once having achieved image registration, access
is gained to temporal information in terms of tech-
niques described earlier. In addition, inter-image
manipulation for the purpose of noise minimization,
for example, by adding two images of the same area
gathered at nearly the same time and for highlight-
ing certain types of changes in the imagery through
ratioing[22] of registered images may also prove
helpful.

A very important additional tape of data pre-
processing is data compression. Data compression
may be desirable to minimize the data volume problem
either in terms of necessity for data transmission
through a given link or in terms of minimizing the
data storage and retrieval problem. Relatively
simple compression techniques based on both spectral
and spatial redundancy appear to be possible at this
time. Compression ratios of 5 or 10 to 1 without
loss of essential information in the data appear
within reach at this time.[27,28]

A most important area and one receiving con-
siderable attention at this time is that of data
display. Since the quantity of data to be dealt
with is typically so large, methods by which to
view it are most important in both pictorially
and numerically oriented systems. Various types
of viewers and image display systems including
those involving color in various ways are being
constructed, marketed, and used especially in the
pictorially oriented field. Though of perhaps
less central importance to the numerically oriented
field, image data display systems are utilized
as effective means by which to monitor processing
system performance and to interact with it. The
most difficult operation of merging ancillary data
with the data stream is often best done this way.
In addition, various types of printers and plotters
are used to present results in map form for the
user's purposes.

Section XI: CONCLUSION

In summary, pattern recognition and the multi-
spectral 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 data gathered on a
spaceborne platform. The manner in which spatial
and temporal variations in the data can be utilized
to increase the quantity and accuracy of informa-
tion 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.
And finally, possible types of preprocessing steps
for both pictorially and numerically oriented
systems were summarized.

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

We hope the reader will find the material of this
Information Note helpful not only in understanding
the multispectral machine processing approach but
in seeing its relationship to other older and more
well-established techniques and in visualizing how
all can contribute to meeting their varied user
needs.

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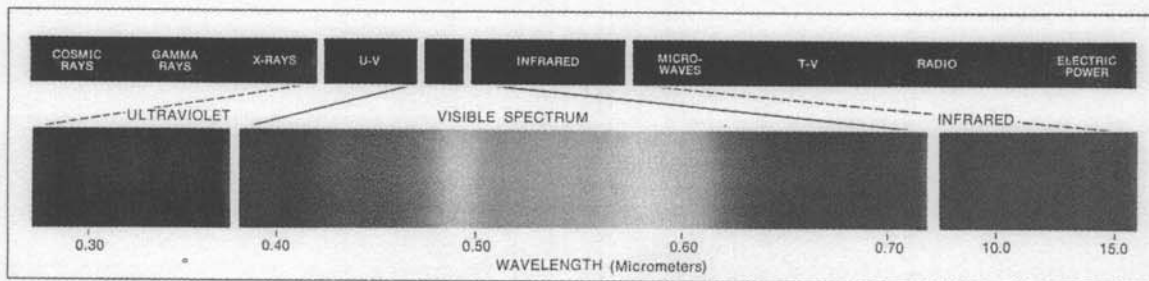
Figure 1. The Electromagnetic Spectrum.

Ephemeral Data
Calibration, etc.

| Sensor System | On Board Processing | Telemetry |

Earth

| Telemetry | Preprossing | Data Reduction Algorithm(s) | Information Consumption |

Ancillary Data

LARS/Purdue
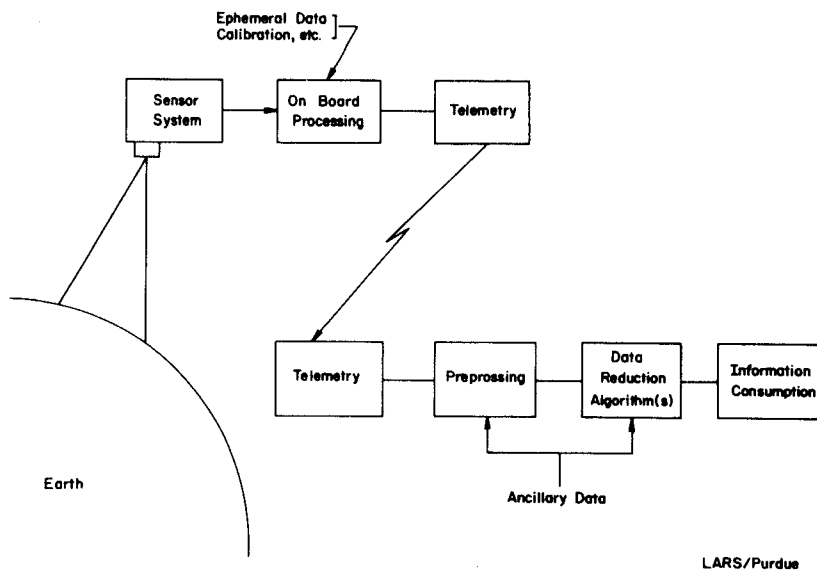
Figure 2.   Organization of an Earth Survey System.

Sun

E Radiation from Atmosphere

Reflected Sunlight

Direct Sunlight

R and E Radiation from Vegetation

Evapotranspiration

Dust and Particles

Scattered Sunlight

R and E Radiation from Vegetation

E Radiation from Ground

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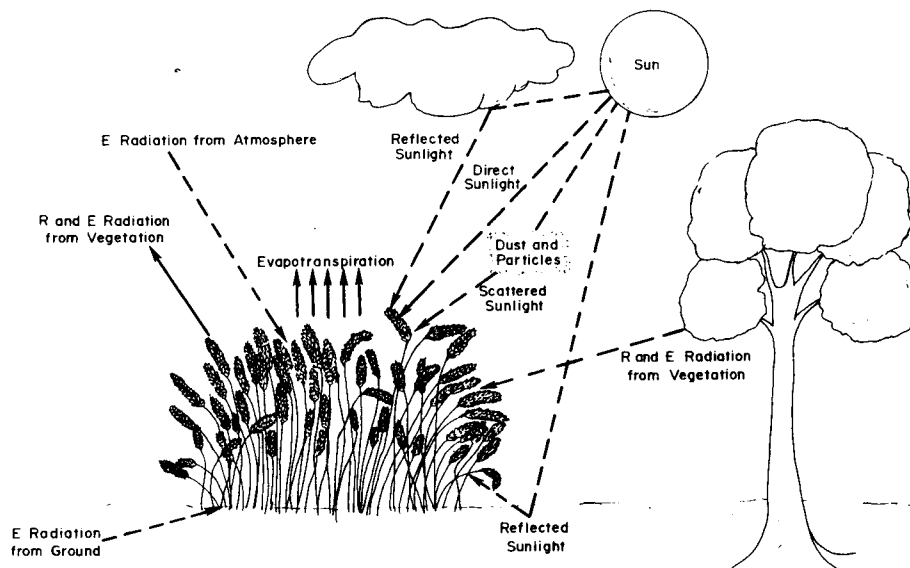
Figure 3.   Reflected (R) and Emitted (E) Radiation Energy Exchange
            in a Natural Environment.

```
┌────────┐      ┌──────────────┐    ┌───────┐      ┌──────────┐
│ Sensor │──────│ Preprocessing│────│ Form  │──────│ Analysis │────────▶  Results
└────────┘      └──────────────┘    │ Image │      └──────────┘
                                    └───────┘
```

Image   Orientation

```
┌────────┐      ┌──────────────┐      ┌──────────┐
│ Sensor │──────│ Preprocessing│──────│ Analysis │────────▶  Results
└────────┘      └──────────────┘      └──────────┘
                    │                      │
                    └───────┬──────────────┘
                        ┌───────┐      ┌──────────┐
                        │ Form  │──────│ Monitor  │
                        │ Image │      │  and     │
                        └───────┘      │ Analysis │
                                       └──────────┘
```

Numerical Orientation
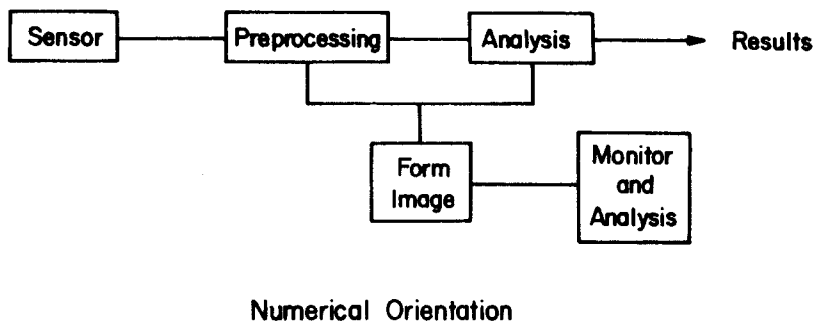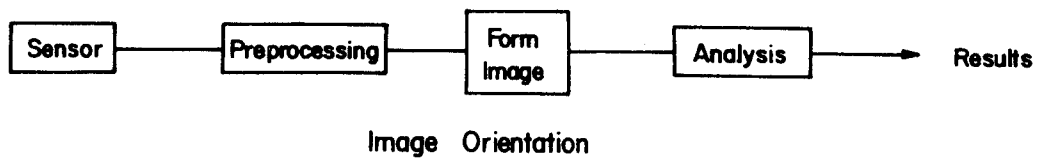
Figure 4.   Organization of Image and Numerically Oriented Systems.

.38 — .44μm   .41 — .47μm

.45 — .52μm   .48 — .56μm   .55 — .64μm

.62 — .68μm   .71 — .79μm   .85 — .89μm
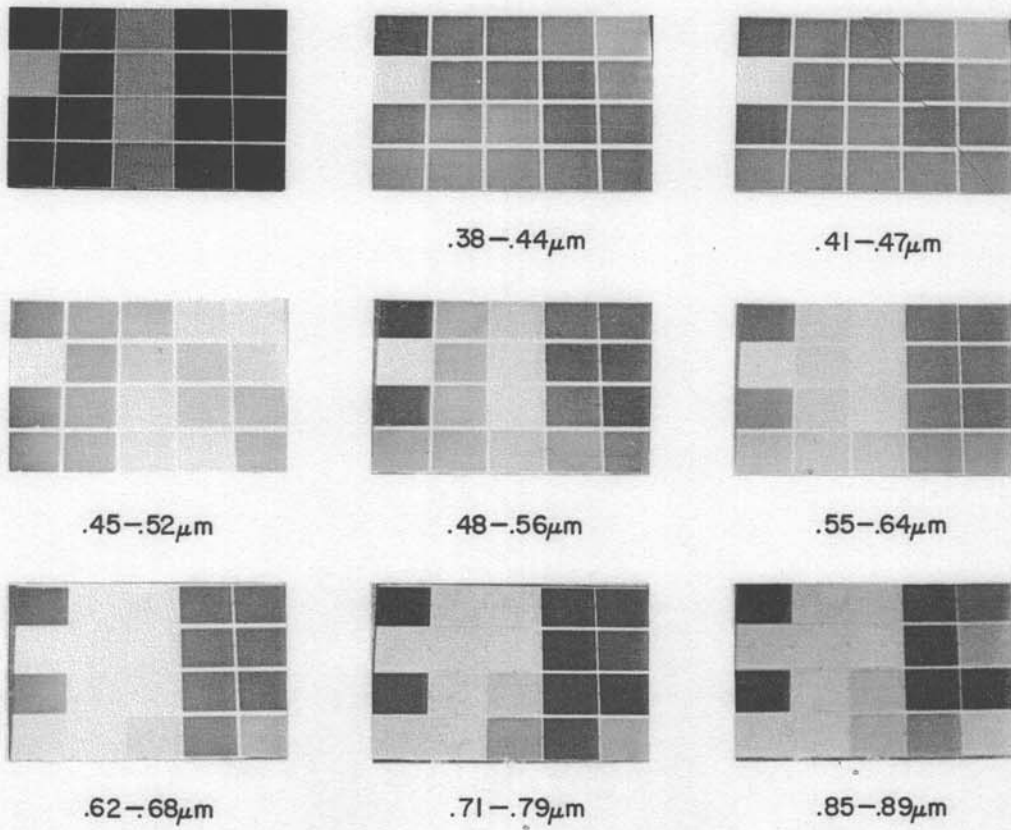
Figure 5. Multispectral Photography of Color Cards.

.4 - .7µm   .7 - .9µm   4.5 - 5.5µm
                                            (Artist's Concept)
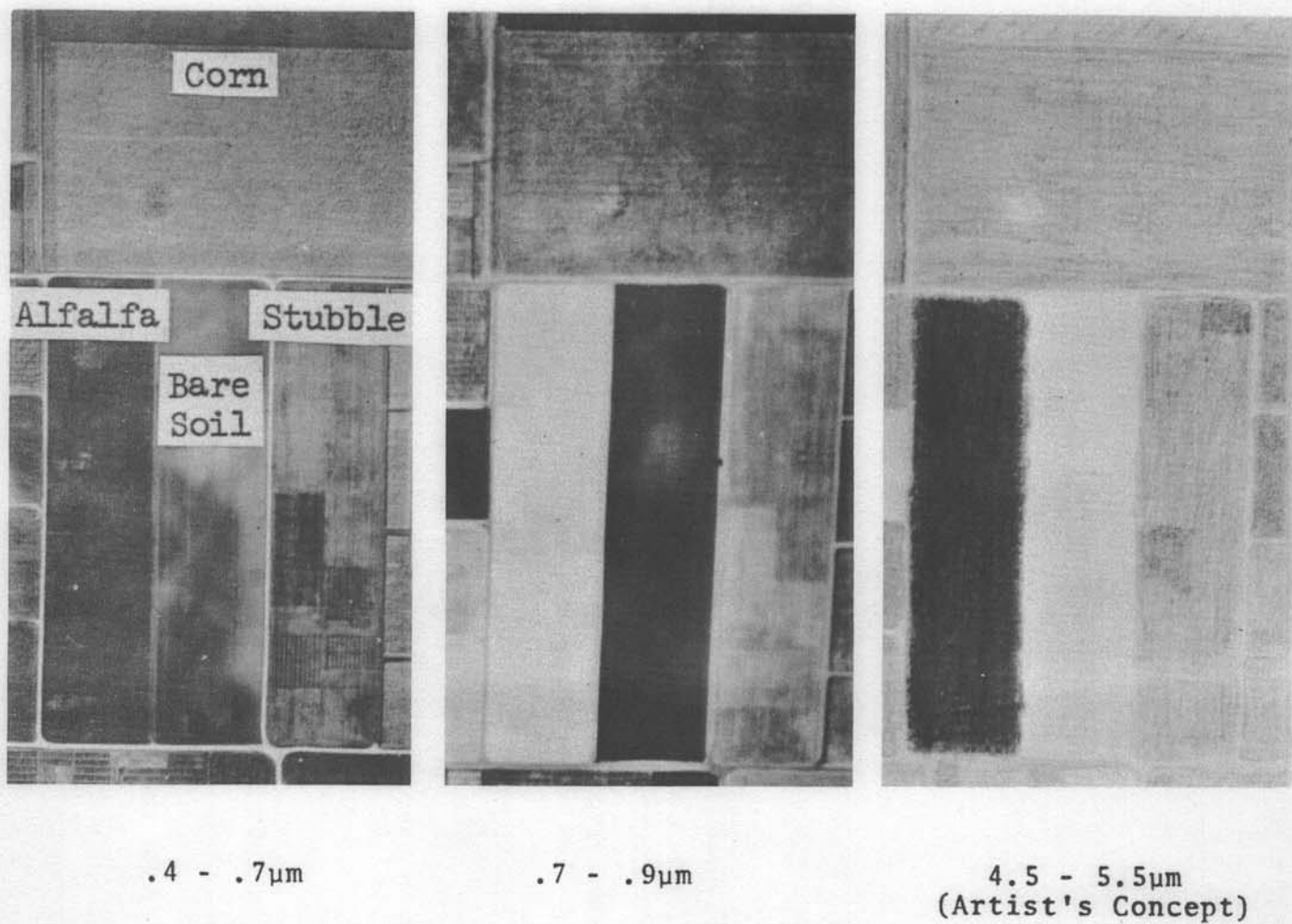
Figure 6.   Multispectral Response of Corn Alfalfa, Stubble,
            and Bare Soil.
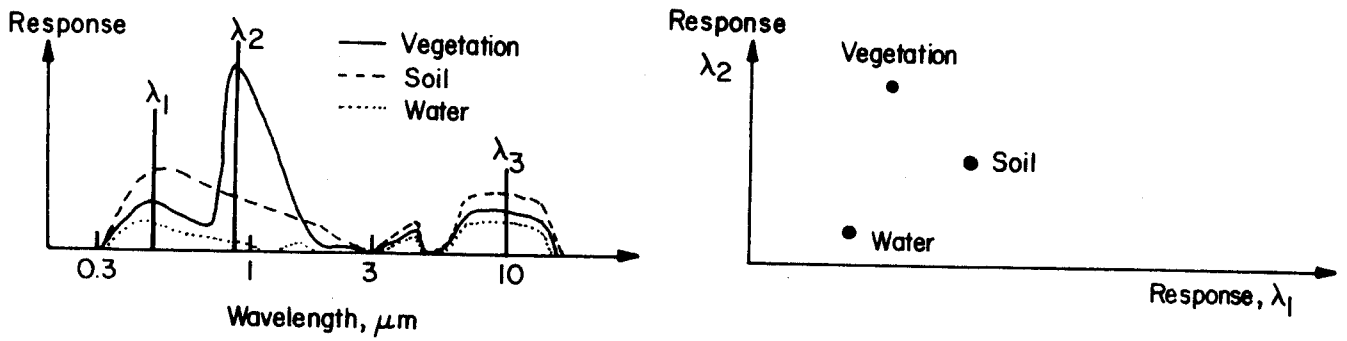
Figure 7.   Spectral Data in Two-Dimensional Feature Space.
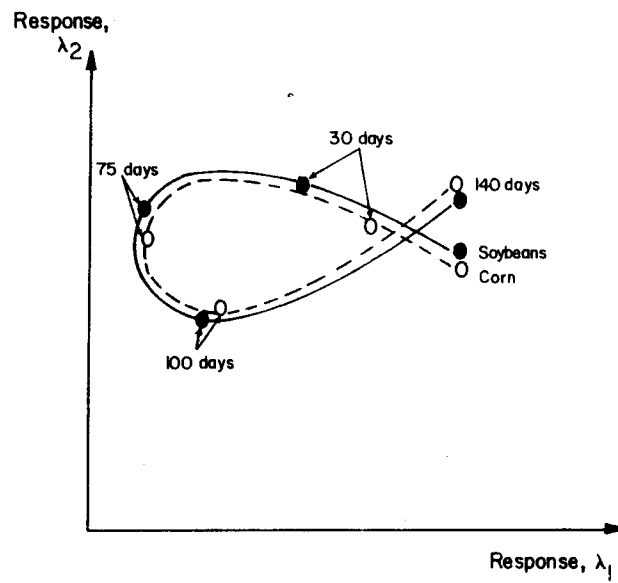
Figure 8.   Temporal Change in Two-Dimensional Feature Space.
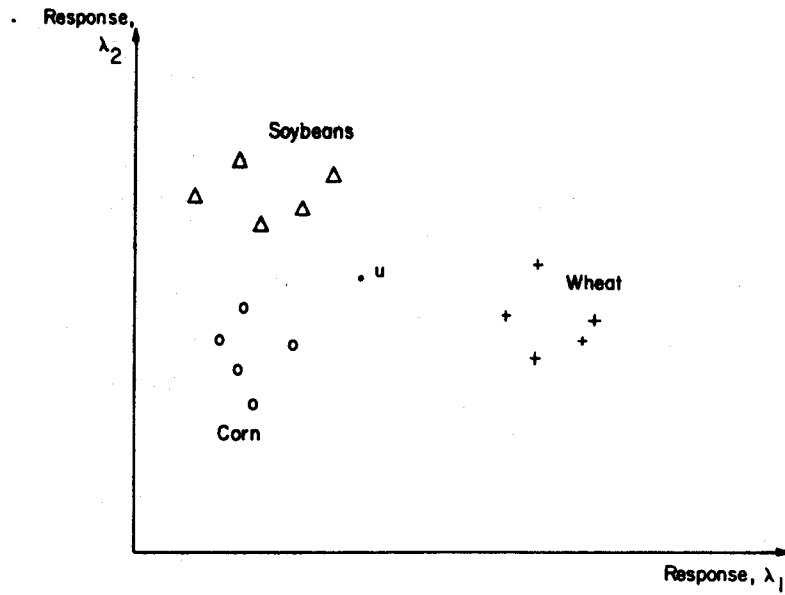
Figure 9. Samples in Two-Dimensional Feature Space.
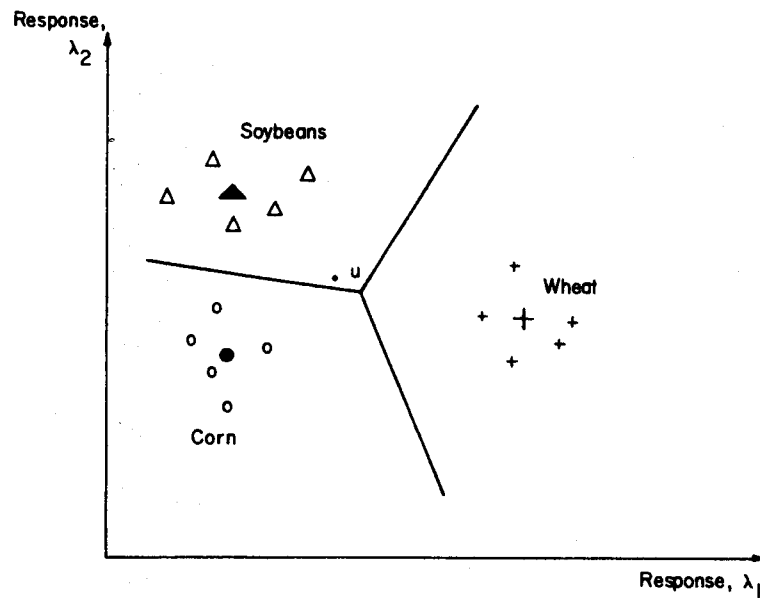
Figure 10. Minimum Distance to Means Classification.
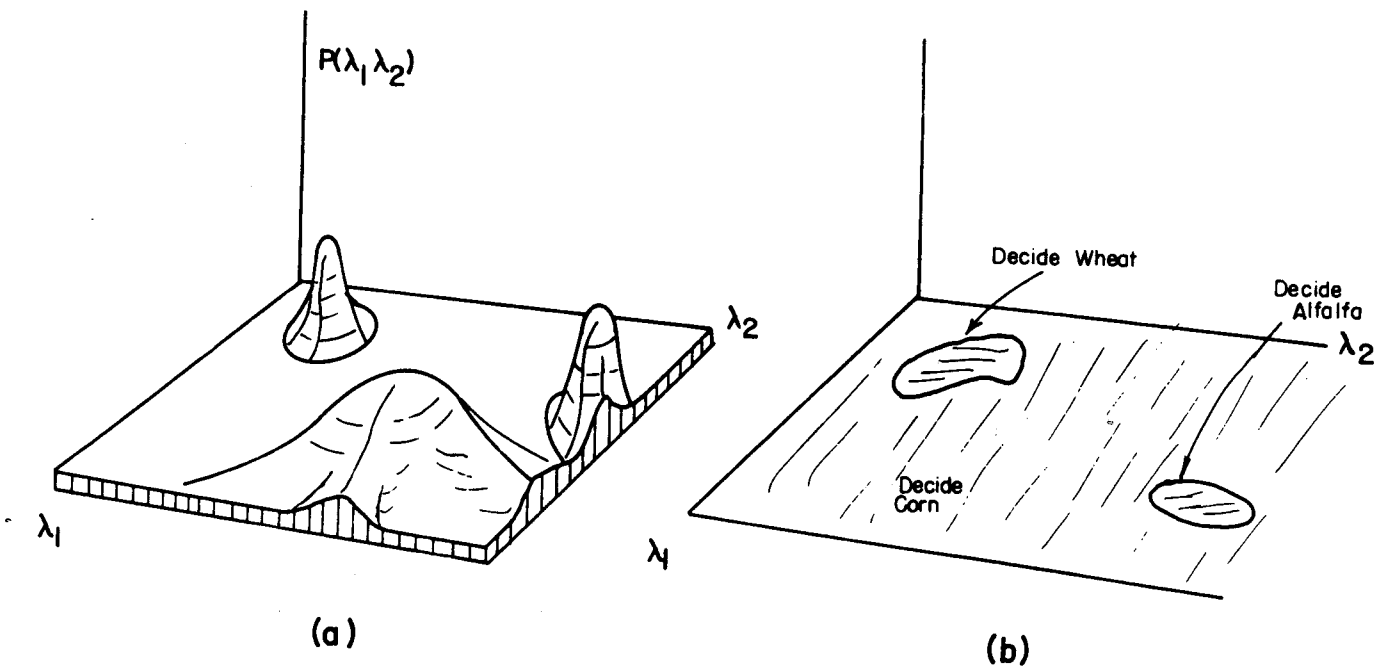
Figure 11. Density Functions and Decision Regions for a Statistical Approach.
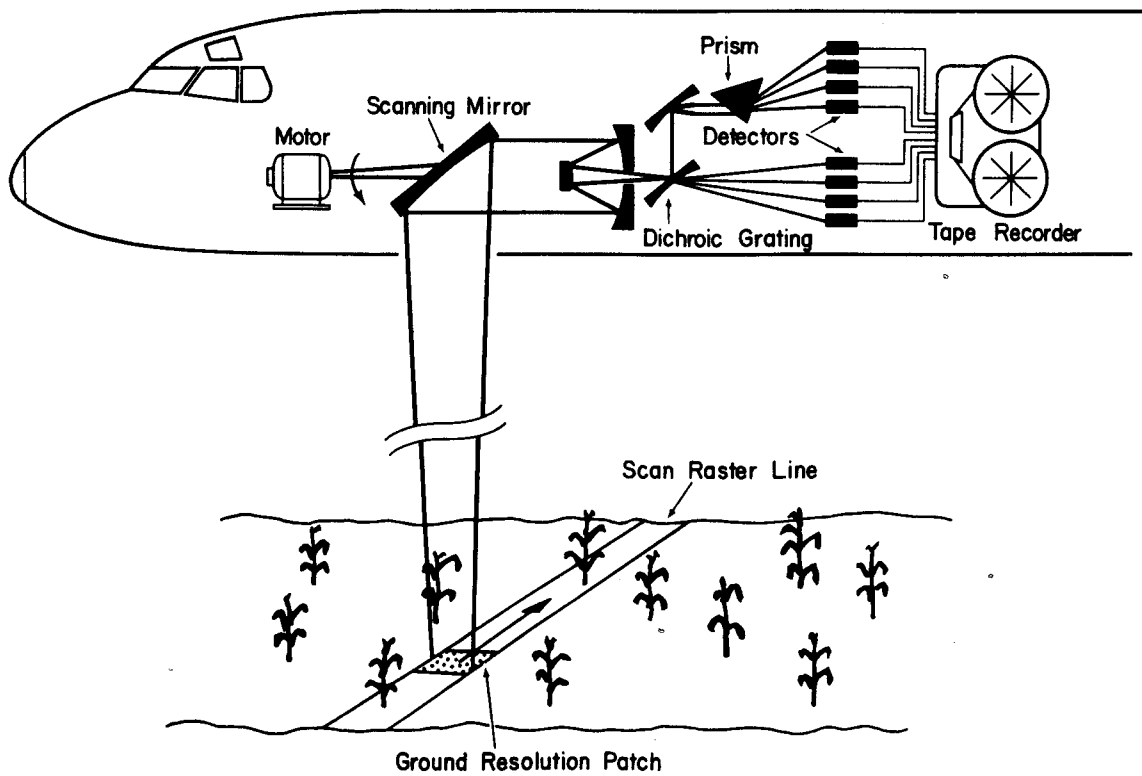
Figure 12. An Airborne Multispectral Scanner.

.72-.80μm
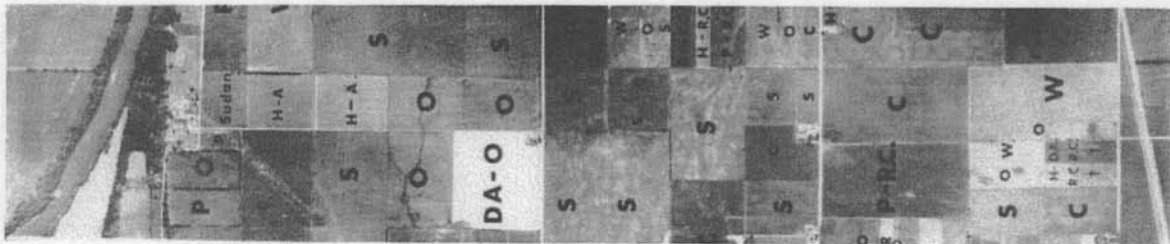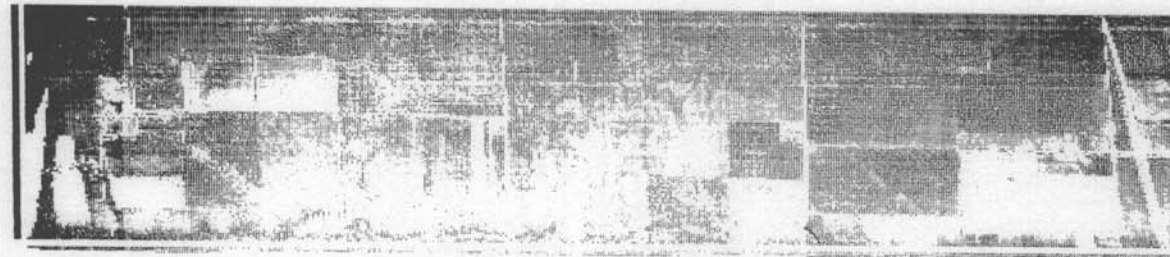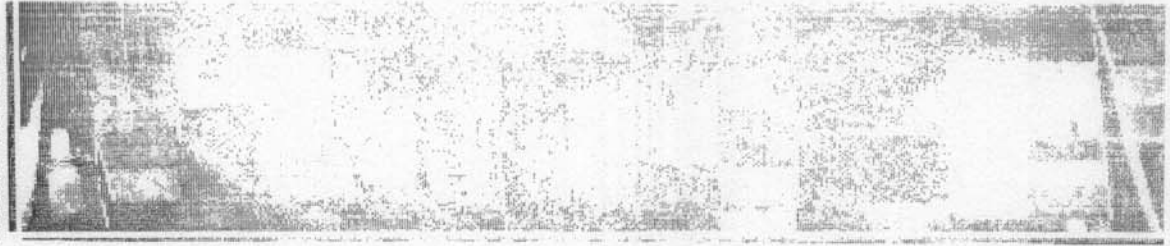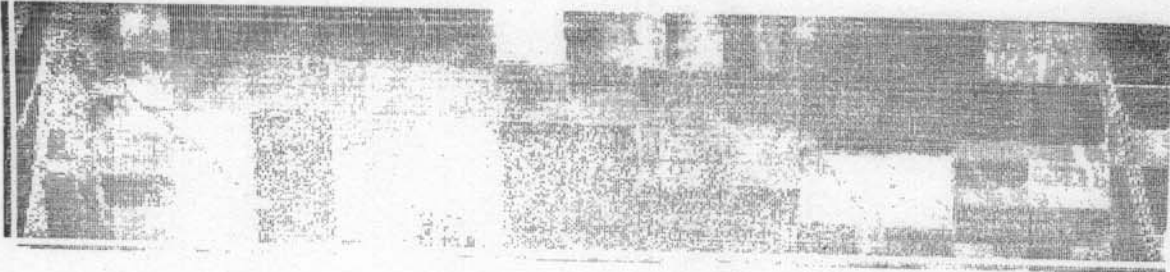
.66-.72μm

Figure 13. Data in Four Wavelengths

.52-.55μm

.40-.44μm
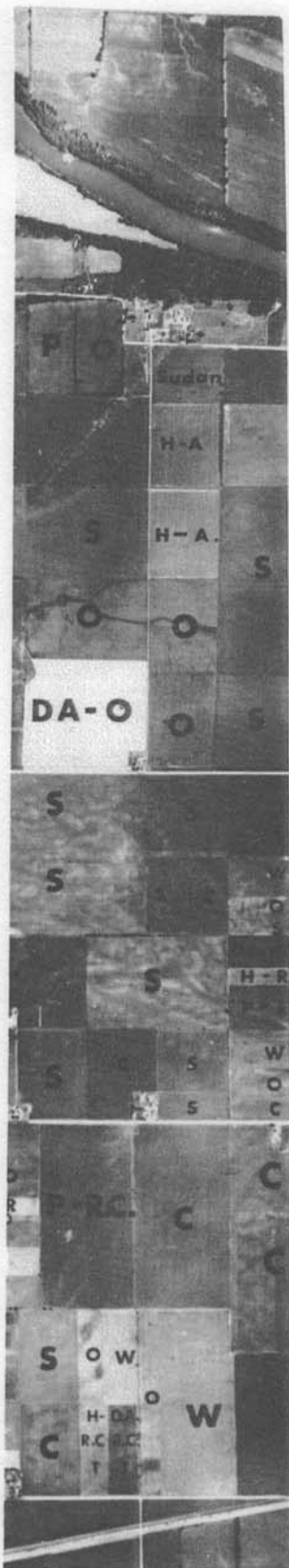
Air Photo
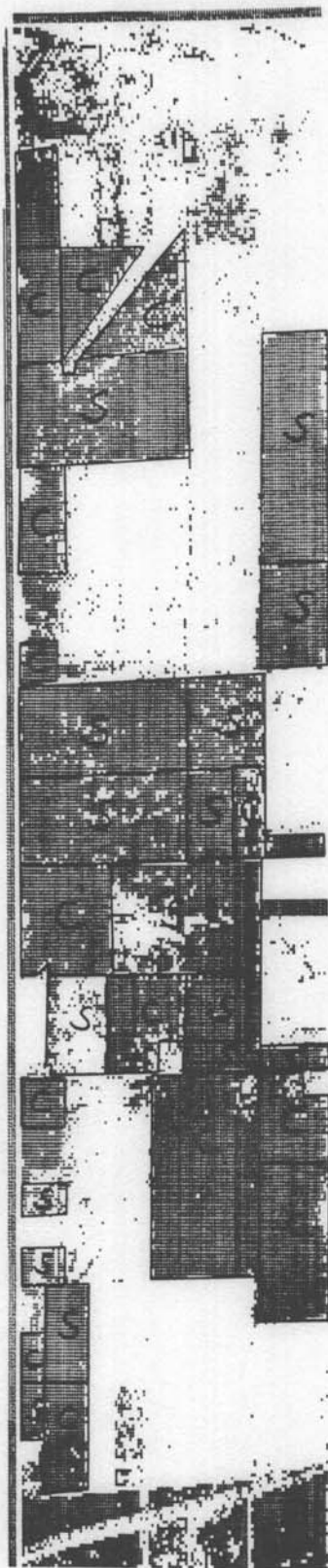
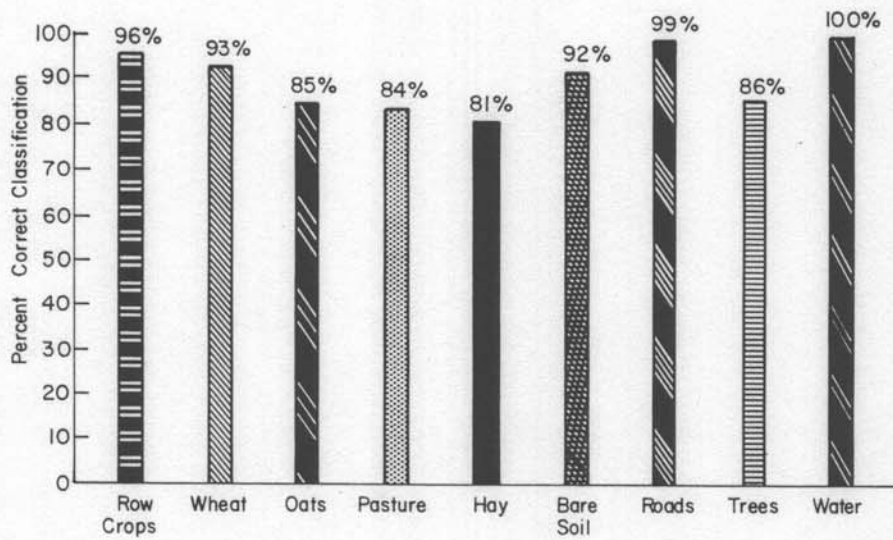| Air Photo | Row Crops (Corn & Soybeans) | Cereal Grains (Wheat & Oats) |
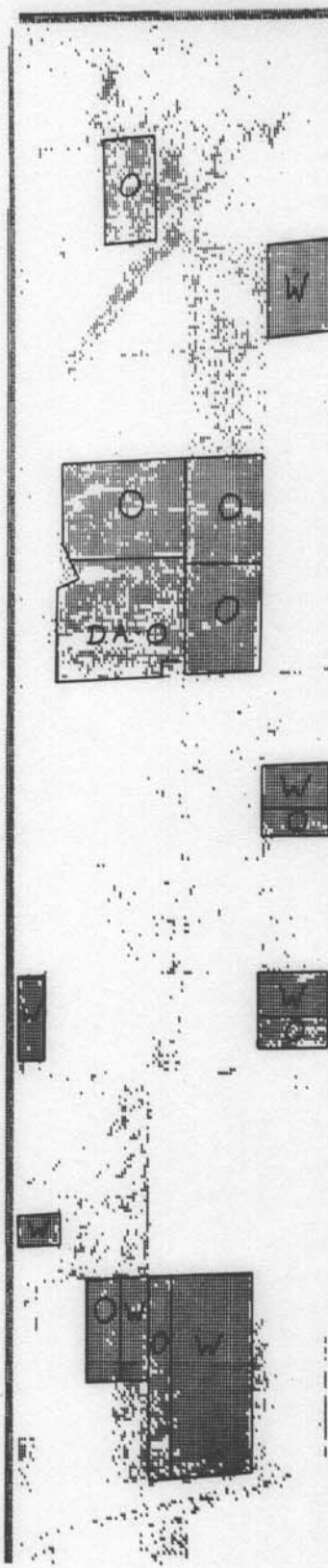
Figure 14.   Spectral Pattern Recognition of Row Crops and Cereal Grains.

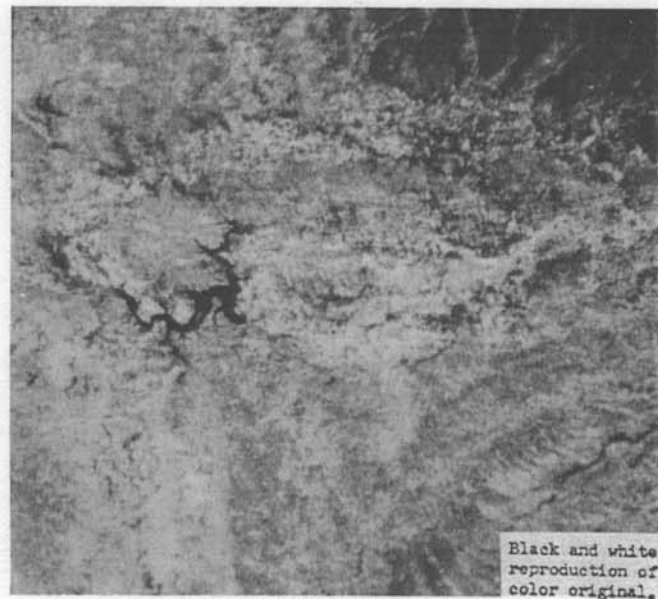Figure 15.   Classification Results for Test Samples.

Figure 16.   Simulated Color Infrared of Texoma Frame.

Black and white
reproduction of
color original.

Figure 17.   Color-Coded Classification Results of Texoma Frame.

Black and white
reproduction of
color original.

Figure 18.   Color-Coded Classification Results of Lake Texoma.

Black and white
reproduction of
color original.
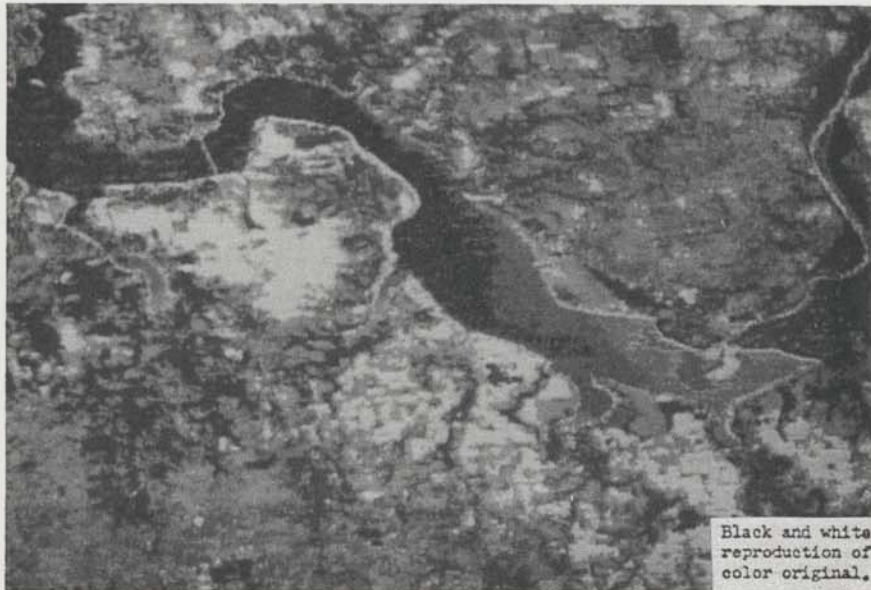
Figure 19. Color-Coded Classification Results of the West End
of Lake Texoma.

Black and white
reproduction of
color original.

Figure 20. Low-Altitude View of West End of Lake Texoma.
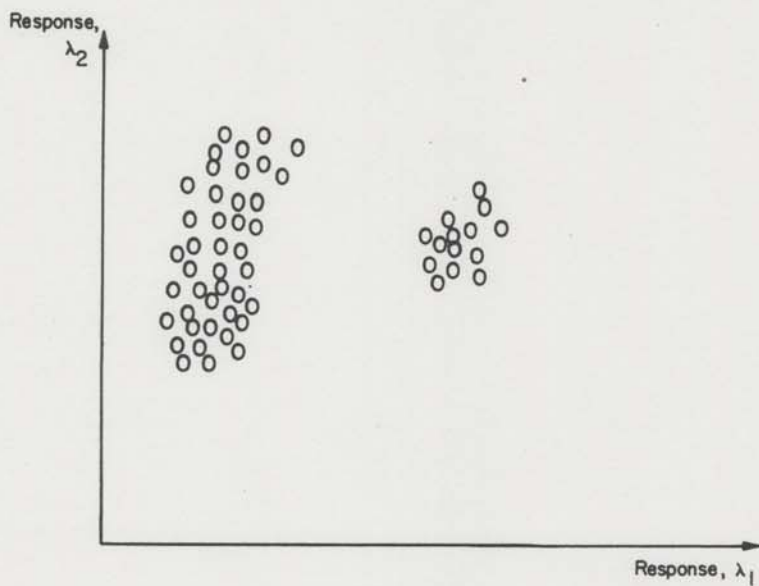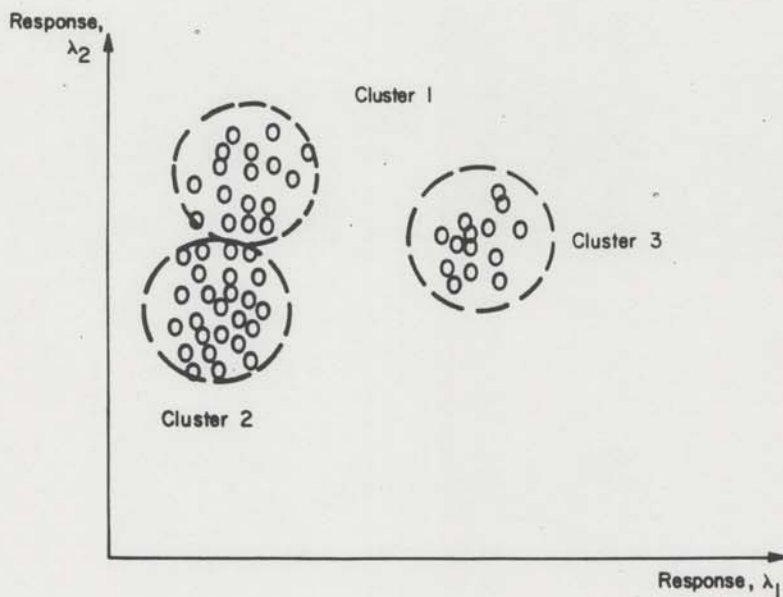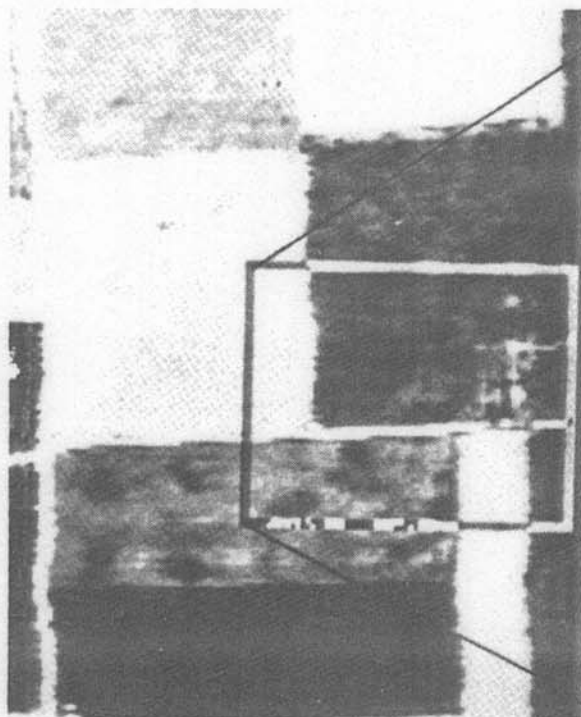
Figure 21. Samples in Two-Dimensional Feature Space.

Figure 22. Clustering in Two-Dimensional Feature Space.

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44444211111111121111112222223555
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44444421111111111111112355545555
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44444421111111111112211122555545555
44444311111111111112223235555555
44444211111111232332212535455555
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Figure 23. Clustered Data Using Four Spectral Bands.

Figure 24. Clustered Data Using Four Spectral Bands.