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Digital Processing of Remotely Sensed Multispectral Data

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ABSTRACT

Although it is well recognized that photointerpretation of the Landsat imagery can provide adequate information for mapping broad categories of land cover at a reconnaissance level, it is also true that the Landsat data in digital format (CCT's) together with numerical (computer-aided) analysis techniques can provide a great deal more information at a higher level of mapping detail with mapping units of approximately half a hectare.

This paper introduces the fundamental concepts involved in numerical analysis of multispectral scanner (MSS) data. Emphasis is placed in the description of the essential steps required to conduct a multispectral classification; that is, I. Pictorial Display of the Raw Data, II. Definition of the Spectral (training) Classes, III. Classification of the Entire Study Area, IV. Pictorial and Tabular Display of the Resulting Classification, and V. Evaluation of the Classification Result.

INTRODUCTION

Since the launch of the first Earth Resources Technology Satellite seven years ago, most of the Latin American countries have utilized the multispectral data obtained by Landsat 1, 2, and 3. Examples of use range from specific studies to evaluate the usefulness of the data to, in a number of instances, operational mapping and quantifying the natural resources of extensive geographic regions. Just recently, a land cover/land use map (Brockmann, 1978) and a geologic map (Pareja et al., 1978) of the entire Bolivian territory (at a scale of 1:1,000,000) have been produced using the Landsat imagery as the basic source of land cover

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information. This basic land cover information was subsequently integrated with other types of information obtained through more conventional means to generate the final maps.

Photointerpretation of the Landsat imagery, particularly the 1:250,000 scale color infrared composite, provides adequate information for mapping broad categories of land cover at a reconnaissance level. However, the Landsat data in digital format (CCT's) contain a great deal more information than its counterpart photographic products. First, the digital Landsat data provide the analyst with a larger number of gray levels with which to work (128 levels in bands 4, 5, and 6, and 64 levels in band 7) in contrast to the 16 or so differentiable graylevels that a normal photointerpreter is able to distinguish in a photographic Landsat product. Furthermore, the digital Landsat data enables the analyst to work with individual minimum mapping units (spatial resolution elements or pixels) of approximately half a hectare in size. Full advantage of digital Landsat data characteristics and more efficient handling of the large quantities of data have been made possible by the development of numerical (computer-aided) analysis techniques. Finally, the numerical analysis techniques offer the advantage of being able to work simultaneously with data from several spectral bands (data represented in multivariate space), which further increases the capabilities of spectrally discriminating objects that in individual spectral bands (data represented in multiple univariate space) would not be possible (Landgrebe, 1978).

This paper introduces the fundamental concepts and essential procedural steps involved in numerical analysis of multispectral digital data. The author's intention in writing this paper has been to condense the most important phases involved in the multispectral classification of remotely sensed data into elemental concepts that would apply to the most readily available multispectral data processing systems.

NUMERICAL TREATMENT OF MULTISPECTRAL SCANNER DATA

The inherently quantitative nature of digital multispectral scanner (MSS) data lends itself nicely to numerical treatment. In remote sensing applications, two major types of numerical treatment of the data are commonly utilized. One is known as <u>image enhancement</u> and the other is referred to as <u>multispectral classification</u>. Due to the large amounts of data involved in remote sensing applications, and since quite often the numerical treatment required in these applications entails complex and cumbersome mathematical transformations, the actual numerical processing is carried out by fast electronic computers.

IMAGE ENHANCEMENT TECHNIQUES

When numerical processing is applied to an image to ameliorate, emphasize or suppress certain features in the image, this type of processing is called image enhancement. There are several image enhancement techniques, examples of which include improving the contrast among high or low gray level objects, emphasizing boundaries between different ground cover types, and suppressing undesired features (noise) in a scene.

The most important aspect of these techniques is that the output is a transformed image with improved visual qualities, which can then be more effectively analyzed and classified through conventional photointerpretation methods.

MULTISPECTRAL CLASSIFICATION TECHNIQUES

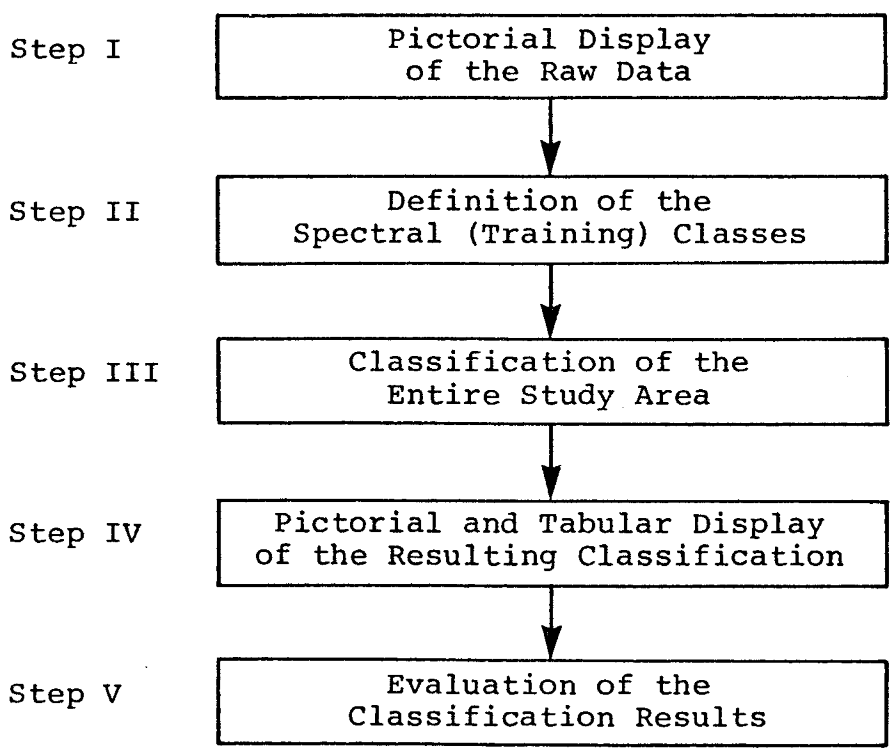
The other type of numerical processing applied to remotely sensed data is the multispectral classification, by which a set of digital multispectral data (for example a portion of a Landsat MSS image) is analyzed and classified into specific classes. The multispectral classification of MSS data implies the definition of a decision criterion that can be used by a computer to assign a certain object in the scene into a specific class on the basis of a given classification rule.

Although the actual multispectral classification of a remotely sensed data set might involve a large number of quite sophisticated mathematical operations (algorithms), the fundamental concepts and essential procedural (analysis) steps can be condensed into a few simple elemental parts. These simple, but important elemental parts of a multispectral classification, will be discussed in detail in the remainder of this paper.

Once the Landsat MSS digital data has been obtained in a computer compatible tape (CCT) format, certain pre-analysis or pre-classification numerical operations can be performed on the data to correct for known geometric and/or radiometric distortions. These geometric corrections, though not always required, are generally done to compensate for the cartographic and planimetric distortions present in a Landsat frame due to the non-polar (quasi-polar) orbital path of the satellite, the earth's rotation during the time that the sensor is recording the data, and the uncertainty of the absolute location of the satellite with respect to a fixed geographic coordinate system.

Radiometric corrections could also be applied to the Landsat data to compensate for selective atmospheric attenuation and differential insolation rates on earth surfaces affected by topographic relief. However, because of the complexity of the problem, atmospheric corrections usually are not applied to Landsat data, and only recently research and testing is being done in the area of radiometric transformations of the data to correct for the effects of topographic relief on the spectral characteristics of earth cover types. Nevertheless, research and experience indicate that to carry out an accurate numerical classification of Landsat data, it is not essential for the data to undergo geometric and/or radiometric corrections.

The basic analysis steps of a multispectral classification are outlined in the flow chart shown below, and a brief description of each one of them follows.



I. Pictorial Display of the Raw Data. Since the numerical MSS data are usually stored in a magnetic tape, the first step in a multispectral classification involves the representation of these data in a pictorial format for visual inspection. This can be accomplished by the use of: (1) a cathode ray tube device (CRT digital display), (2) a line or dot-matrix printer/plotter, or (3) an optical film writer.

The data thus represented in a pictorial format is then used to:

(a) assess the quality of the data,
(b) determine the amount and distribution of cloud cover in the scene,
(c) delineate areas of interest for detail study, i.e. stratify the entire Landsat frame into subregions which could be in the form of arbitrary quadrangles, areas within a particular watershed, a province or county, and
(d) select representative samples within the area of interest to define the spectral (training) classes that will be used for training the classifier.

The most important and critical part in this step is to make sure that all possible objects present in the scene are properly represented in the training sample.

II. Definition of the Spectral (Training) Classes. We all know that computers do not reason or make their own decisions. They do only what they are told (programmed) to do. The process of telling the computer how and in what circumstances to make certain classification decisions is known as "training".

In the particular case of classifying a remotely sensed multispectral data set, the computer has to be provided with the characteristics of a number of spectral (training) classes to enable the computer to decide whether or not an unknown data sample (pixel) should be classified into one of the training classes. In practice, the spectral characteristics of ground cover types are usually defined by simple statistical parameters, such as the means and covariances of normal (Gaussian) distributions of the spectral response of each one of the training classes.

There are two major approaches to determine the spectral characteristics of all the ground cover types in which the entire data set is to be classified, i.e., (1) the supervised approach, and (2) the unsupervised approach.

Supervised Approach. When the statistical parameters that define the training classes are determined through the selection of homogeneous and informationally pure fields of known cover types, the procedure is called supervised training approach. The advantage of this approach is that it is simple and straightforward. However, when Landsat (and in general any type of coarse spatial resolution) data is to be classified, the supervised approach has several drawbacks, due to:

(1) the difficulty of finding the exact location and large enough fields of a homogeneous known cover type. This is particularly true in Landsat data gathered over Latin America where the "minifundio" (small land holdings) agricultural practice accounts for a large percentage of the cultivated areas.

(2) the requirement of good quality reference (ground truth) data collected concurrently with the gathering of the Landsat data, which in practice is a difficult task to be accomplished.

(3) the fact that a large number of the spatial resolution elements (pixels) of a Landsat data set cover more than one homogeneous (pure) ground cover type, and therefore, the spectral characteristics of these pixels do not match any of the pure spectral classes defined by the supervised approach. Consequently, these "mixture" pixels are likely to be classified erroneously since their spectral characteristics are not properly represented in the training set.

Unsupervised Approach. In the unsupervised approach, the statistical parameters that define the training classes are determined through the selection of heterogeneous fields containing as many different spectral responses as possible, and then a clustering algorithm (Wacker, 1969) is used to automatically group pixels of similar spectral characteristics into a number of spectrally separable cluster classes. In this approach, the identity of the cluster (training) classes need not be known *a priori*, and perhaps the most important feature of this approach is that it will define not only the pure ground cover types in the scene, but also the mixture classes that are usually present in a Landsat data set. Therefore, a closer representation of the natural spectral groupings in a Landsat scene are obtained through the unsupervised approach.

Figure 1 shows a plot of the spectral responses in a two-dimensional space (Landsat bands 5 and 6) of a large number of data points (pixels) corresponding to the three basic ground cover types, i.e. water, soils, and vegetation. Note how the points corresponding to one of these three basic cover types group themselves (form a cluster) around a common center point. The clustering algorithm finds these clusters and computes their characteristic statistical parameters, which are then used to train the classifier.

The concept of spectral separability (Swain and Wacker, 1971) is of paramount importance in the multispectral classification of Landsat data because the accuracy of the final classification results is a function of the degree of spectral separability among the training classes (Swain and King, 1973). There are several complex criteria to measure the spectral separability among training classes, however, the fundamental concept underlying the most commonly used spectral separability measures is quite simple. Figure 2 shows graphically the relationship between a measure of spectral separability and the statistical parameters that define a spectral training class. Note that essentially the spectral separability is proportional to the distance between the mean of the two training class distributions and inversely proportional to the sum of their standard deviations.

Effective techniques to define representative training classes using the unsupervised approach have been developed (Fleming _et al._, 1975). However, the most important element required _to define_ the optimum set of training classes is still the input from the analyst and the ultimate user. In other words, the best results are obtained through _Computer-Aided_ Analysis Techniques in contrast to _Automatic_ Data Processing Techniques.

It should be emphasized that the definition of the training classes is the most critical step in the entire multispectral classification sequence. It is during this analysis step that the analyst has to relate the _spectral classes_ (defined by the unsupervised approach) to the actual cover types present on the ground, i.e. the _informational classes_. This is not an easy and straightforward task because there are many instances in which there is not a one to one correspondence between the spectral classes and the conventionally defined informational classes. On the other hand, this might not be a great problem in countries where there is not yet a well-established conventional classification scheme and where there is a willingness to utilize a land cover classification scheme based primarily on the spectral characteristics of the different ground cover types.

III. Classification of the Entire Study Area. In this step of the analysis sequence, the computer implemented classifier does practically all the work, once it has been told what to do. It is at this stage that the statistical parameters that define the spectral characteristics of the training classes are used in training the classifier and thus perform the classification of the entire study area. The classifier is a decision-making algorithm that can be trained to assign each and every pixel (of a remotely sensed scene) to one of the predefined training classes according to an appropriate classification rule (Swain, 1978). There are various types of classifiers and they differ from one another in the type of decision or classification rule used, such as the maximum likelihood per-point classifier, minimum distance classifier, layered classifier, cascade classifier, ECHO (Extraction and Classification of Homogeneous Objects) classifier, levels classifier, and the context classifier. Since it is outside the scope of this paper, the above mentioned classifiers will not be described here. Suffice it to say that the computer implemented classifier can classify large numbers of data points (large geographic regions) of a multispectral (several bands) data set in a relatively short time. Once the entire study area has been classified, the resulting classification is usually stored in computer compatible tapes ready for display.

IV. Pictorial and Tabular Display of the Resulting Classification. After the completion of the multispectral classification, the results can be displayed in several different formats according to the user needs and specifications. There are two major types of display formats: (1) pictorial and (2) tabular. For example, the classified area could be displayed as a map of a certain scale, projection, and minimum mapping unit. The different classes (ground cover types) can be represented by (1) alphanumeric symbols (Figure 3), (2) graphic symbols (Figure 4), (3) gray levels (Figure 5), (4) boundary lines (Figure 6), or (5) different colors. The classification results also could be displayed in a thematic map format in which only one class is represented. The other major type of classification display format, i.e. the tabular format, can be utilized when a user requires only information such as areal extent (acreage) or percentage of each one of the different cover types present in the study site.

V. Evaluation of the Classification Results. For a multispectral classification to be of practical use, it is necessary to determine its accuracy and reliability. Using the numerical analysis approach, it is possible to quantitatively assess the degree of accuracy of a multispectral classification. Experience has shown that the test field performance method is most effective. Test fields of known cover types are randomly selected; the computer then analyzes every pixel in the test fields and determines the percentage of correctly classified pixels.

SUMMARY AND CONCLUSIONS

Although photointerpretation of satellite multispectral imagery provides useful information for inventorying and managing natural resources, numerical (computer-aided) analysis of this imagery, such as multispectral classification, allows a great deal more information to be extracted from the data. A multispectral classification involves five essential analysis steps: (1) pictorial display of the raw data, (2) definition of the spectral (training) classes, (3) classification of the entire study area, (4) pictorial and tabular display of the resulting classification, and (5) evaluation of the classification results. The usefulness, accuracy, and reliability of the classification results depends primarily upon the proper definition of the spectral classes used for training the classifier. To properly train the classifier, the analyst must, to a certain extent, understand the physical basis of remote sensing, digital representation of the data, extraction of information principles, and applications of the resulting information for solving real-life problems. In other words, the multispectral classification results will be of value to the user only to the extent that the analyst recognizes how to best combine the attributes of man and machine in a truly symbiotic relationship. Or, as stated by Landgrebe (1978[1]), "It really is a question of teaming man with machine, and learning which tasks man can do better and which the machine."

With the above considerations in mind, it can be concluded that to effectively transfer the numerical remote sensing technology, education and training of human resources should play a fundamental role in the overall transfer process.

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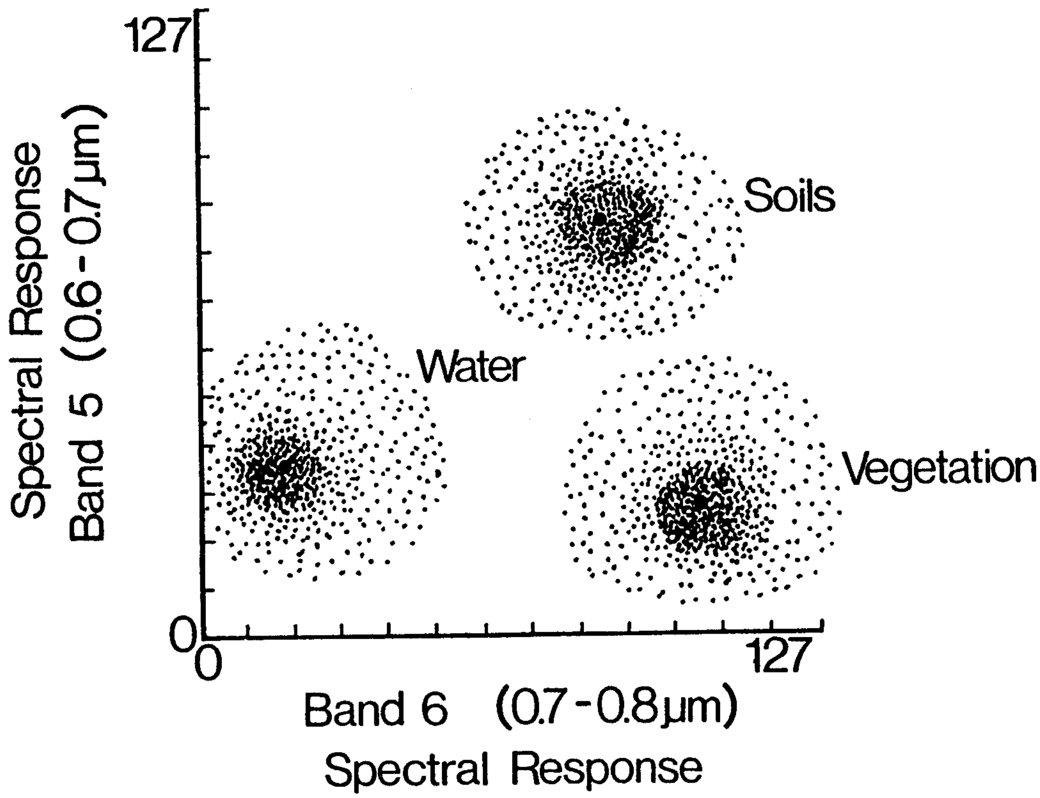

Figure 1. Plot of the Spectral Responses of Water, Soils, and Vegetation in the Landsat Bands 5 and 6. Note how the spectral responses of each one of these major ground cover types form "clusters" around a common center.

$$\text{SEPARABILITY} \propto \frac{\mu_B - \mu_A}{\sigma_A + \sigma_B}$$

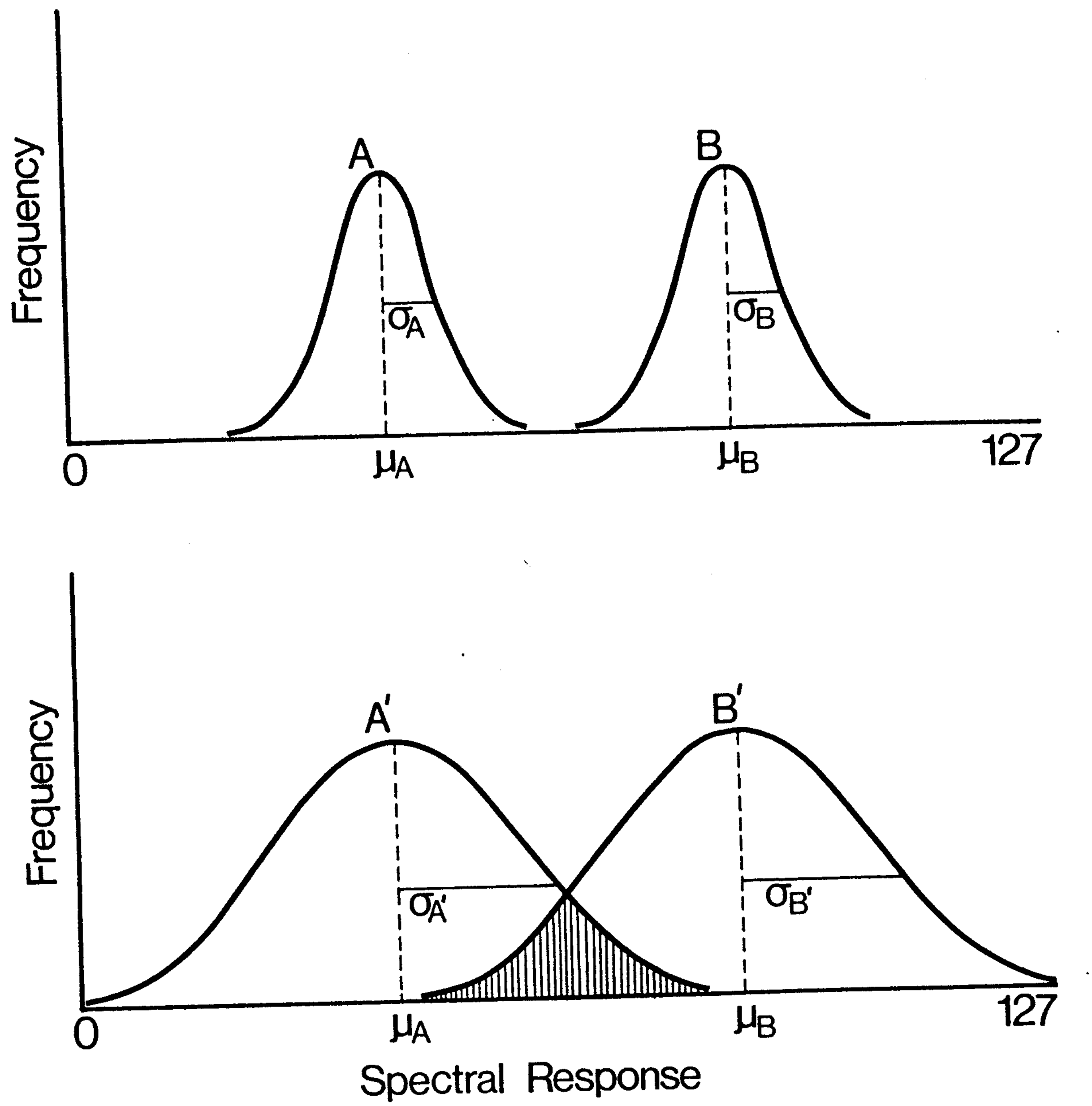

Figure 2. Graphical Representation of the Relationship Between the Spectral SEPARABILITY and the Means (μ) and Standard Deviations (σ) of Spectral Class Distributions.

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W - Water

/ - Grass

- Soils

A - Chaparral

= - Forest-1

I - Forest-2

- Sand

Figure 3. Alphanumeric Representation of a Final Multispectral Classification.

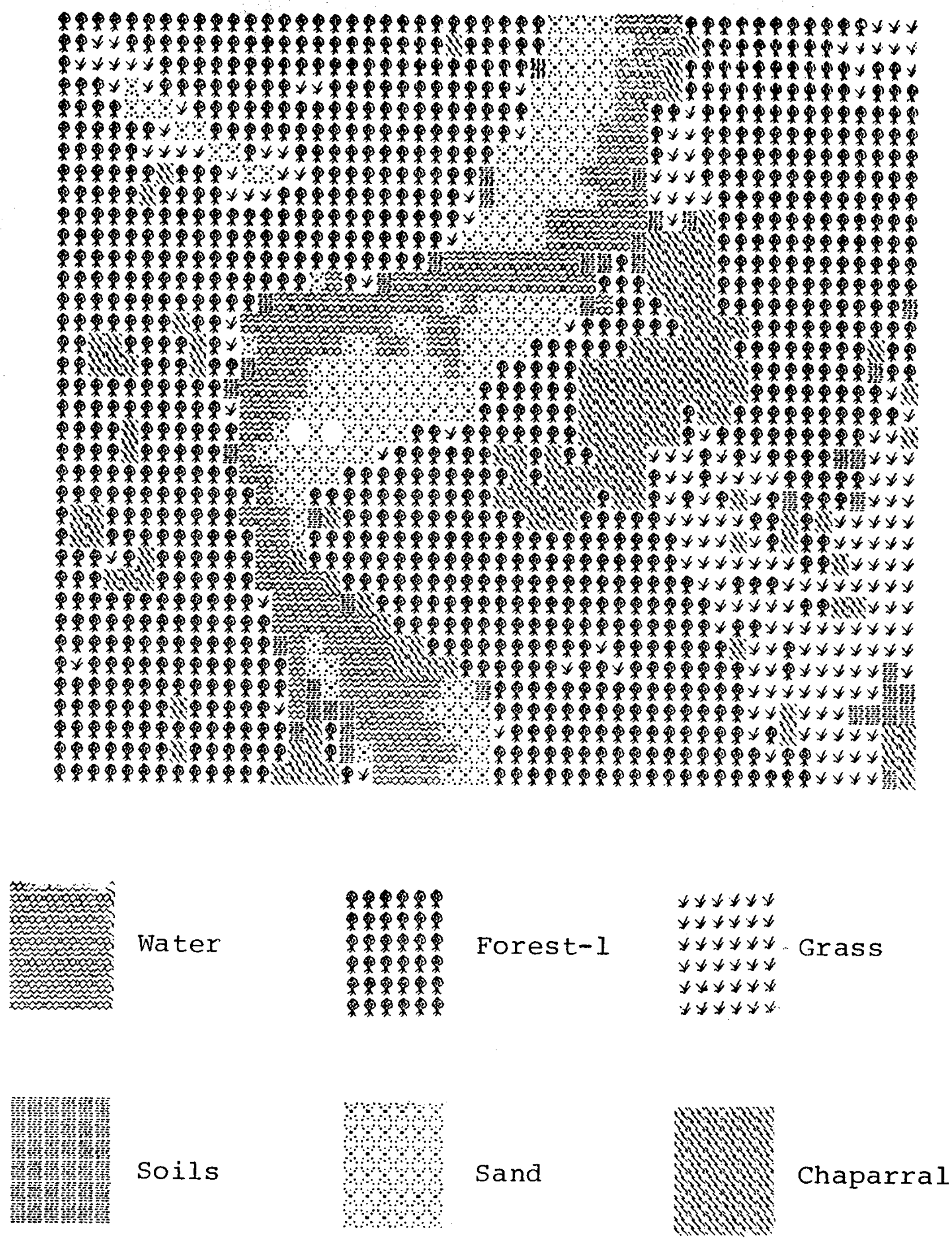


Figure 4. Graphic Symbols Representation of a Final Multi-Spectral Classification.

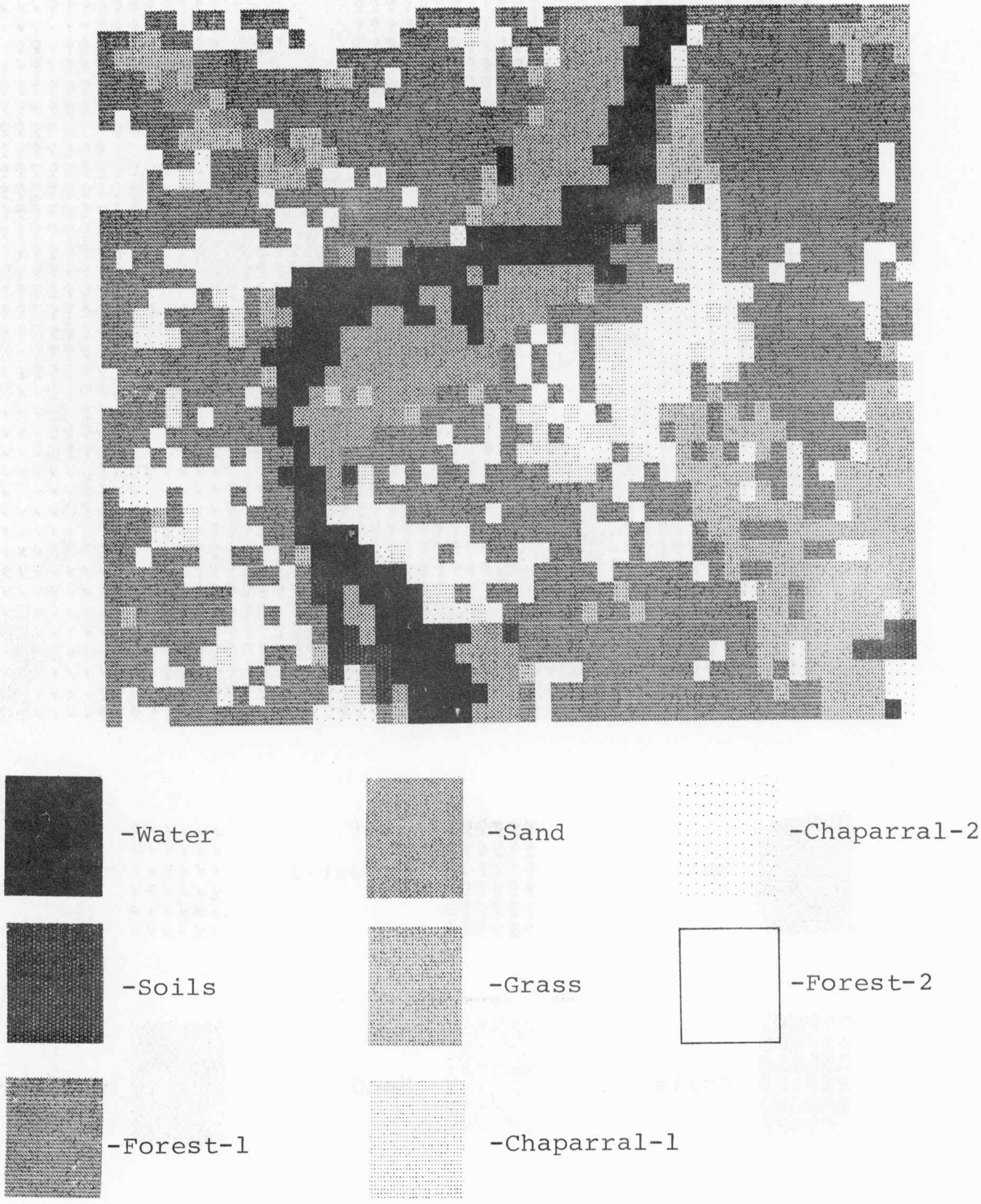
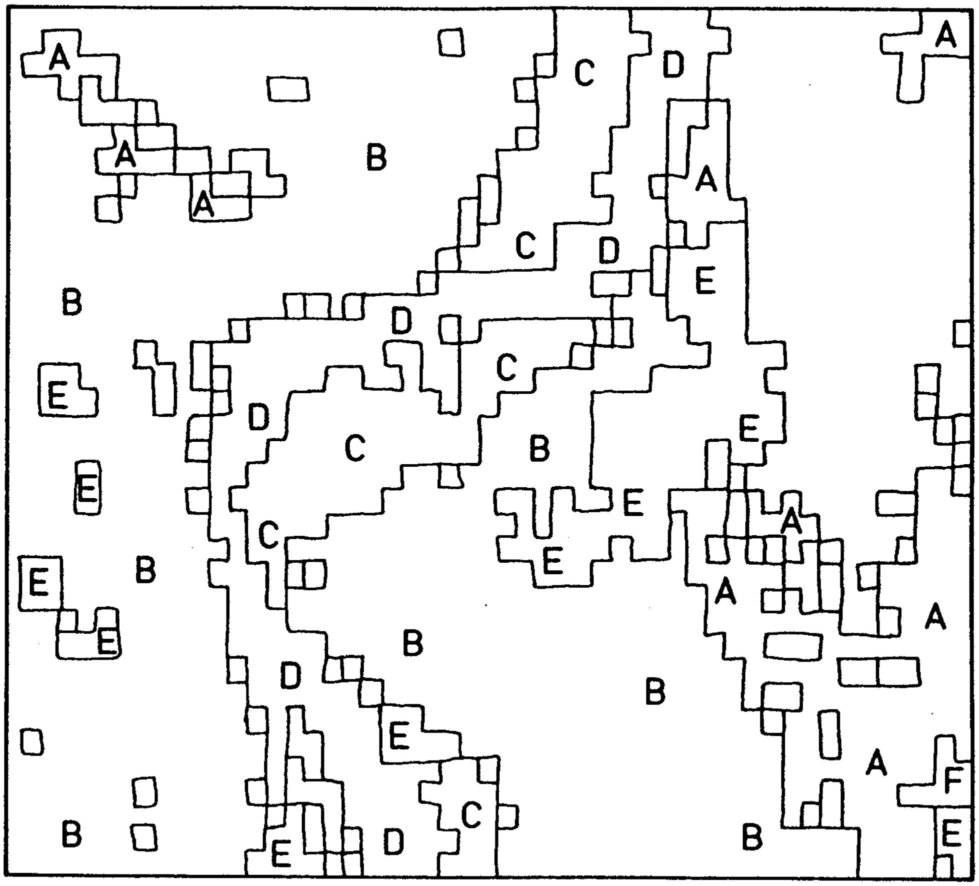


Figure 5. Gray Levels Representation of a Final Multispectral Classification.



A - Grass

B - Forest-1

C - Sand

D - Water

E - Chaparral

F - Soils

Figure 6. Boundary Lines Representation of a Final Multi-spectral Classification.

BIOGRAPHICAL SKETCH

Luis A. Bartolucci

Luis A. Bartolucci, born and raised in Santa Cruz, Bolivia, received his B.S., M.S. and Ph.D. in Geophysics from Purdue University. He has been involved in Remote Sensing research since 1969 at the Laboratory for the Applications of Remote Sensing/Purdue University, where he is currently Technical Director of Technology Transfer Programs. He has played an active role in the development of remote sensing technology for applications in the area of water resources and has also made outstanding contributions in the field of thermal infrared radiation for remote sensing applications. Dr. Bartolucci has served as consultant to the U.S. Information Agency, the U.S. Agency for International Development, the Interamerican Development Bank, and to several Latin American development agencies. He has been Principal Investigator and Project Director of several domestic and international research and training programs involving computer-aided processing and analysis of remotely sensed data for earth resources inventories, and is the author of over thirty scientific publications in the area of remote sensing. His primary research activities involve the application of remote sensing techniques for water quality assessment and snowcover mapping, spectral signature mixing problems, topographic influence on the spectral response of ground cover types, radiometric calibration of Landsat data, and the design of integrated information systems for developing countries.