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COMPUTER-AIDED ANALYSIS OF REMOTE SENSOR DATA: MAGIC, MYSTERY, OR MYTH

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MAGIC, MYSTERY, OR MYTH?

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ABSTRACT

The launch of the Landsat-1 satellite in 1972 initiated a new era in the collection, interpretation, and analysis of remotely sensed data. Early results indicated that the synoptic coverage and digital format of the Multi-Spectral Scanner (MSS) data provides considerable potential for a variety of earth resource applications. During the past seven years, much has been learned about both the capabilities and the limitations of this satellite data, as well as the analysis techniques for processing such data. It is clear that there are no "magical" techniques for automatically processing Landsat data to obtain highly accurate and reliable results under any and all circumstances! Computer-aided analysis of MSS data requires an effective man/machine interaction that involves an analyst who is knowledgeable of the data and scene characteristics, as well as the processing techniques utilized. There are, however, many aspects of computer-aided analysis that are still not adequately understood, either in theory or in practice.

This paper addresses some of the mysteries and the myths which have often been associated with computer-aided analysis of remote sensor data. Results of several studies involving aircraft, Landsat, and Skylab MSS data are examined. The value of using topographic, soils, or other data sources in addition to MSS spectral data is discussed, as are the potentials for utilizing Synthetic Aperture Radar (SAR) and Thematic Mapper (TM) MSS data sources.

Key Words: Landsat, Thematic Mapper, Computer-Aided Analysis, Multi-Spectral Scanners, Forest Cover Mapping

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I. INTRODUCTION

It is rather obvious that high flying aircraft or satellites can obtain enormous quantities of data over vast geographic areas in a relatively short period of time. Such masses of data can be collected using a variety of sensor systems, each of which has its own particular advantages, as well as disadvantages. However, there is a major step between the collection of the data and the reduction of this data into useful information! A key factor in applying remote sensing technology therefore, involves the data analysis techniques that can most effectively reduce the masses of data collected into the type of information which is required by the user.

Development of multispectral scanner (MSS) systems during the past fifteen years has resulted in an entirely new dimension in data collection systems and processing and analysis techniques. Because data from MSS systems can be easily quantified and subsequently processed by a digital computer, and also because the format of multispectral data is ideally suited for pattern recognition analysis, there has been particular interest in defining effective computer-aided analysis techniques for processing this type of data. This interest has grown rapidly since 1972, when the first of the Landsat satellite MSS data became available. During these past seven years, many computer processing and analysis techniques have been developed and tested for a variety of disciplines and conditions. The general thrust of most of this research has been directed at defining and developing techniques to map and tabulate various earth surface features over large geographic areas in a timely, cost-effective manner. This work has been conducted on a wide range of test sites, by many different people, using a variety of processing and analysis techniques. There have been hundreds of articles published, and it would appear that, as in many other areas of research, we are "learning as we go"; testing many concepts, rejecting some, accepting others. This paper will examine some of the capabilities and limitations, and the associated "myths" and "mysteries," that have been encountered to date in the development of computer-aided analysis techniques.

The procedures for digital processing and analysis of data from multispectral scanner systems can be defined as involving five primary areas of activity:

- Data Reformatting and Preprocessing,
- Definition of Training Statistics,
- Computer Classification of Data,
- Information Display and Tabulation, and
- Evaluation of Results

These five areas of activity will be used to provide a framework for much of the following discussion. In considering these aspects of remote sensing, we will first look at some of the terminology involved and the misconceptions (or perhaps, "myths") that have developed around these terms.

II. MISLEADING TERMINOLOGY

Automatic Data Processing (ADP) is a term that has often been applied to all phases of processing and analysis of multispectral scanner (MSS) data. Procedures for reformatting and preprocessing MSS data do not involve any data analysis per se, but simply involve changing the characteristics of the raw data so that it is in a better format for the analysis sequence. Such data handling procedures can be precisely defined and are carried out by the computer in a rather straight-forward, fairly automatic mode of operation. As such, this phase of the sequence could be correctly referred to as automatic data processing. However, to classify MSS data by computer in order to obtain maps and tables of the various cover types requires that the computer be "trained" to recognize particular combinations of numbers (reflectance measurements in each of the wavelength bands) that hopefully will characterize each of the cover types of interest. Experience has shown that an effective man/machine interaction is needed to develop training statistics that will result in classifications having the highest accuracy and reflecting the interests and needs of the user. Thus, an integral, key part of the classification process is the requirement for an analyst who is: (1) knowledgeable of the classification techniques as well as the theory involved, (2) who is familiar with the spectral, spatial and temporal characteristics of the cover types in the area being analyzed, and (3) who also has an understanding of the users' requirements.

Classification of Landsat or other MSS data is far from being an "automatic" process, and the use of the term "ADP" really does not give a correct impression of what is actually involved. I believe that it is better to use terms such as "computer-assisted" or "computer-aided analysis techniques" (CAAT), in order to give a more correct impression of the role of the analyst relative to that of the computer.

Another rather common, and often misused remote sensing term is "spectral signature." As often used, this term implies a unique, well-defined and characteristic spectral pattern by means of which a particular earth surface feature can be positively and reliably identified. However, all green vegetation, for example, has rather similar, basic spectral characteristics, which makes it difficult to define unique "spectral signatures" for every individual species of vegetation of interest. In addition, normal geographic and temporal effects as well as other factors may cause variations in the spectral behavior of any species or cover type at any point in time. Thus, it should be recognized that unique and unchanging spectral signatures do not exist in the natural world. However, at any point in time in a particular geographic area, there may exist measureable spectral response patterns from the various vegetation types of interest that are distinctive enough in that particular data set to allow various cover types to be identified.

The misunderstandings that have resulted from use of the term "spectral signature" have sometimes led to proposals to develop large data banks of spectral signatures which would then be used as a source of training data to analyze incoming sets of MSS data collected at any time of the year and from any geographic location. Archives of spectral data are useful for studying spectral characteristics of earth surface features, but do not appear to be a feasible solution to defining training data sets for computer classification of MSS data obtained under a wide variety of conditions and geographic areas.

Because of the many misunderstandings that have developed, the term "spectral signature" should be used with caution, or perhaps a completely different term, such as "spectral response patterns" should be used instead.

III. THE "MYTH" THAT "BIGGER IS ALWAYS BETTER!"

In many aspects of life, including the world of research, we often fall into the trap of thinking that "bigger is better," even though we all know that this is not always true! In the area of computer-aided analysis of remotely sensed data, there is a tendency to use all of the available wavelength bands for the classification. It would appear that this attitude has developed as a result of the Landsat MSS having only four bands, and the fact that computer classifications involving only four bands are relatively fast. In the near future, however, Thematic Mapper data, having seven wavelength bands, will become available. Should all seven be used for computer classification? What impact will the larger number of wavelength bands have on the classification accuracy and cost (i.e., computer time)?

Earlier studies with both aircraft and satellite data indicate that simply increasing the number of wavelength bands does not improve classification performance, but the cost of processing the data can increase significantly as more and more wavelength bands are involved. Figure 1 is a good example of the relationship between number of wavelength bands used and the resulting classification performance and also the computer time required. The data used in this study were obtained by the ERIM 12-channel aircraft scanner, and the cover types included deciduous forest, coniferous forest, corn, soybeans, forage, and water. Another study involving Skylab S-192 MSS data also indicated that more wavelength bands do not necessarily produce increased accuracy of the classification. In this study, "major cover types" (coniferous forest, deciduous forest, grassland, exposed rock and soil, water, and snow), as well as individual "forest cover types" (Douglas and white fir, ponderosa pine, Engelmann spruce and subalpine fir, aspen, Gambel oak, grassland, water and snow) were classified. As one might expect, the major cover types could be classified more accurately than the individual forest cover types. At both levels of detail, however, classification accuracy did not increase when more than four wavelength bands were used (Figure 2). The more important result, however, in both of the above studies, involves the spectral location of the wavelength bands used, rather than just the number of bands. Analysis of the aircraft data indicated that the middle infrared portion of the spectrum (1.3-3.0 μm) was particularly important, while the Skylab study indicated that the near infrared (0.7-1.3 μm) was especially valuable for

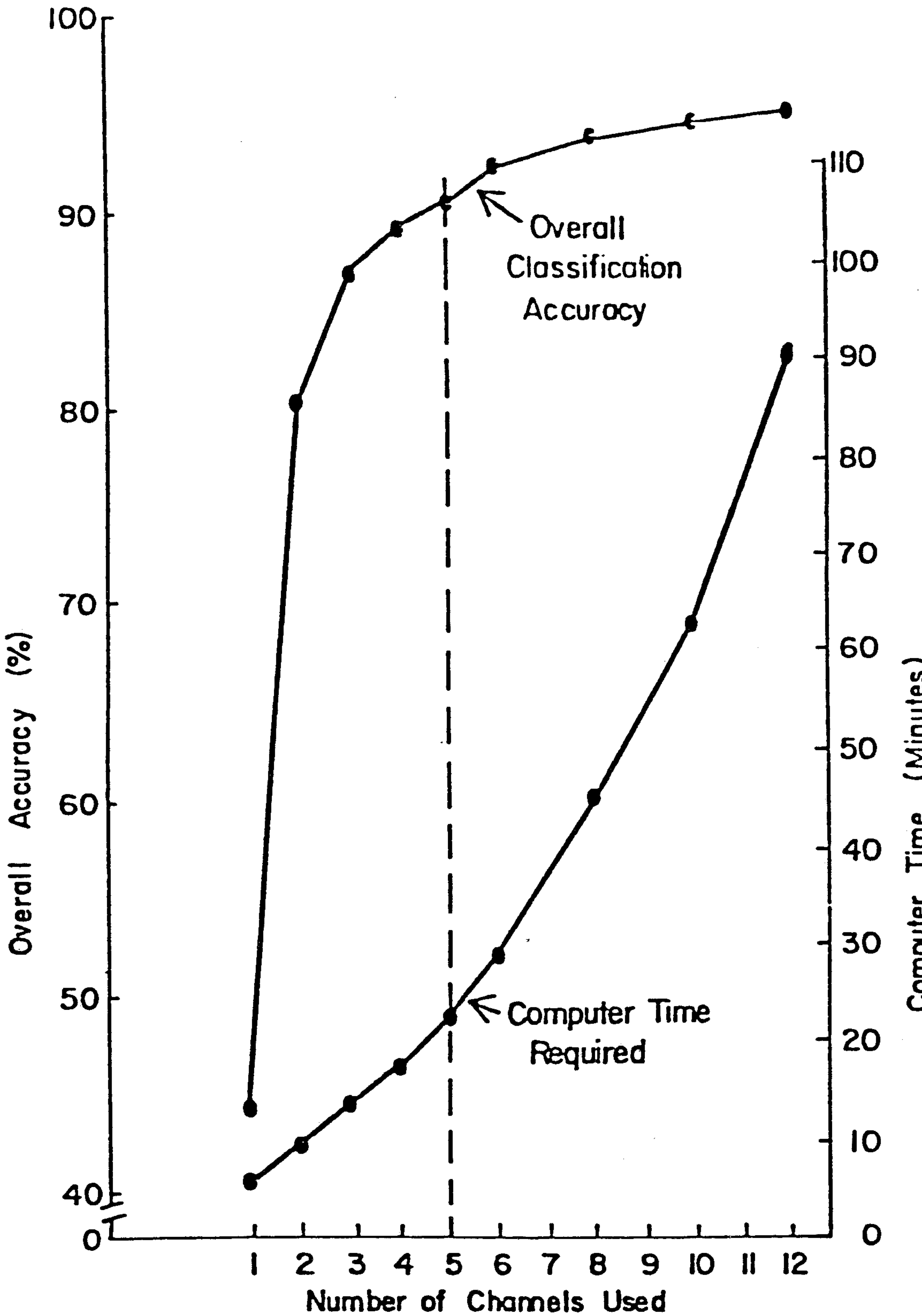

Figure 1. Overall classification accuracy and computer time required versus number of channels used (aircraft MSS data). (From Coggeshall and Hoffer, 1973.)

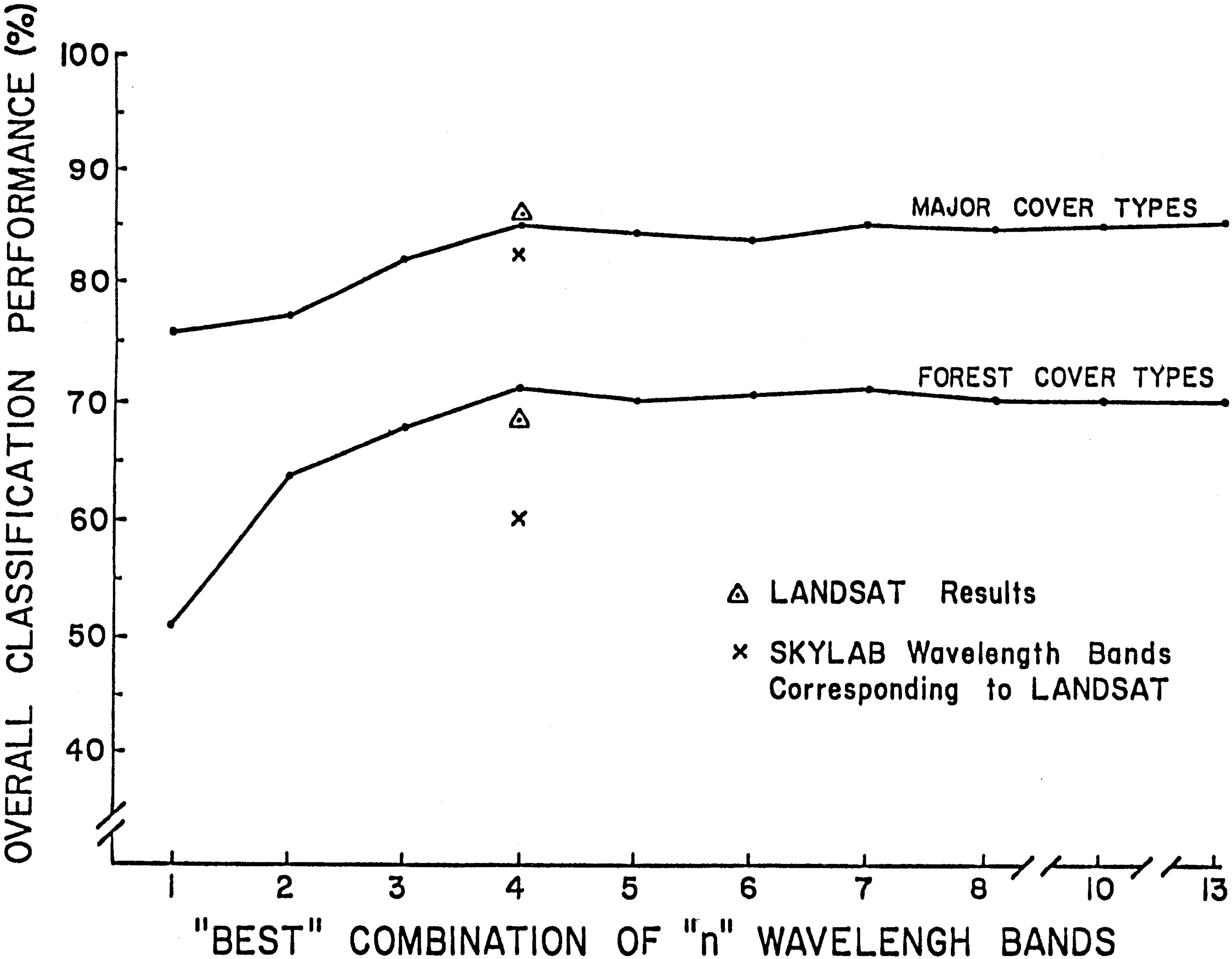

Figure 2. Overall classification performance versus number of wavelength bands used (Skylab data). (From Hoffer, et al., 1975b.)

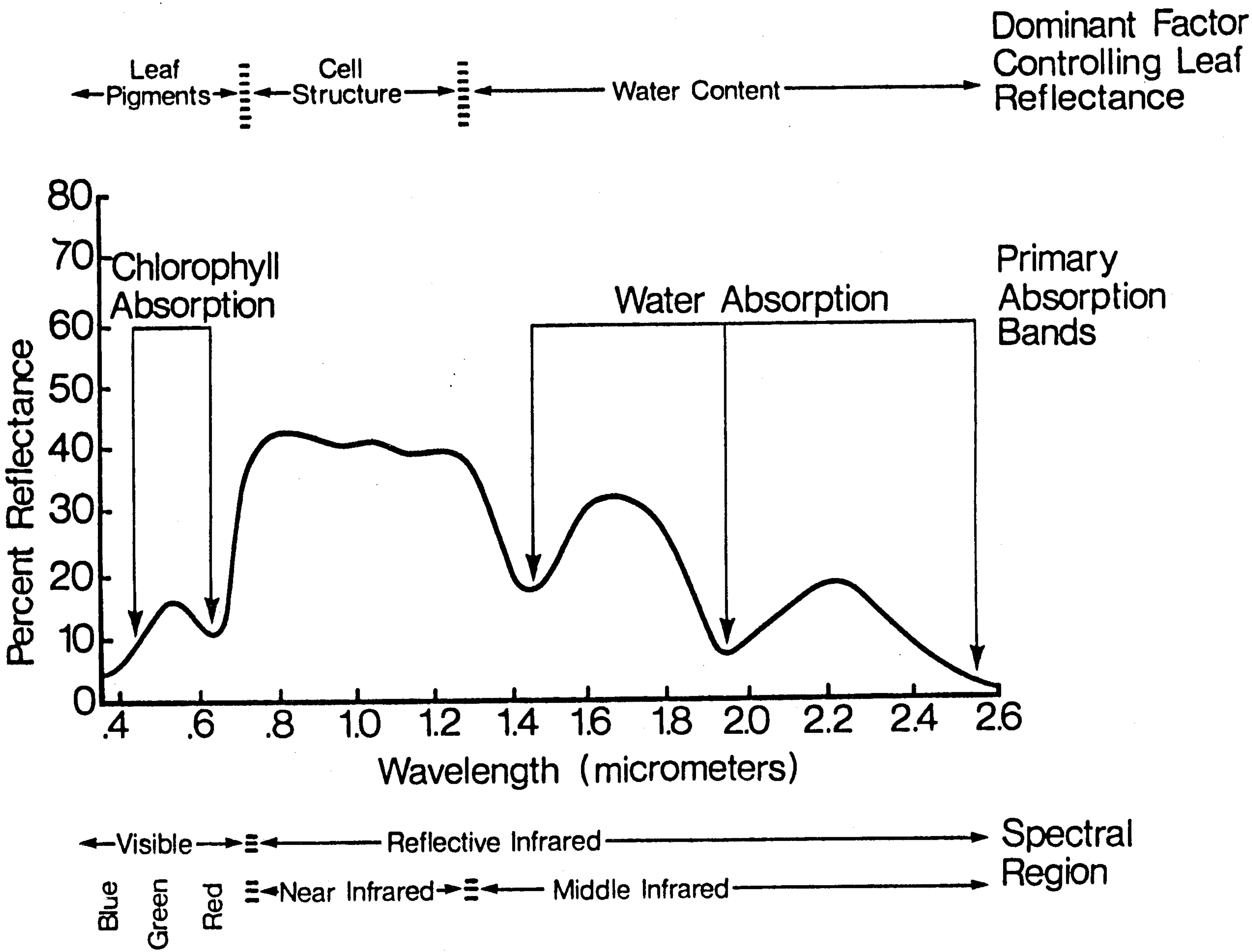

Figure 3. Reflectance characteristics of green leaves (after Hoffer and Johannsen, 1969).

identifying forest cover type. As shown in Tables 1 and 2, in both studies, when the optimal combination of six wavelength bands were selected (using the LARSYS Feature Selection Processor), all four of the major regions in the optical portion of the spectrum were represented (i.e., visible [0.4-0.7 μm], near infrared [0.7-1.3 μm], middle infrared [1.3-3 μm], and thermal infrared [3-14 μm]. Even when only four wavelength bands were used, three of the four major regions in the optical portion of the spectrum were represented. This is significant when one considers the very different energy/matter interactions that take place in the different regions of the spectrum (Figure 3).

The results of these studies have several implications concerning future MSS systems and the computer-aided analysis of data from such systems. These include the following:

(1) The spectral location and width of the wavelength bands used can significantly influence the accuracy of the cover type classification.

(2) A relatively few (e.g., 4-6) properly located wavelength bands can enable classifications to be obtained that are as accurate as those obtained using all (e.g., 12-13) available wavelength bands.

(3) At least one wavelength band in each of the near infrared, middle infrared, and thermal infrared wavelength regions and two bands in the visible wavelengths appear to offer the optimal combination to spectrally differentiate and identify various vegetative cover types.

(4) Detailed cover type classes (e.g., individual forest cover types) cannot be classified as accurately as more generalized cover type groups.

(5) Increased numbers of wavelength bands can cause significant increases in computer CPU time required, but classification performance may not significantly increase when more than 4-6 bands are utilized.

(6) The improved spectral resolution and the spectral location of the wavelength bands defined for the Landsat-D Thematic Mapper should enable significant improvements in classification performance over those obtained with previous 4-channel Landsat MSS systems.

In addition to being able to understand and define the optimal numbers and locations of wavelength bands for computer classification, there are also data compression techniques, such as principal components, which can be used very effectively to condense most of the information content of many wavelength bands into a relatively few (e.g., 3-4) number of channels of data. It would appear that such techniques have considerable promise, but that they need to be studied and tested more, particularly in situations where multitemporal data is involved.

Table 1. Wavelength Band Selection Sequence and Classification Results Using Aircraft MSS Data[1]

No. of Channels Used	Test Area Classification Results[2]	Wavelength Bands Selected[3]	Number of Bands in Each Major Wavelength Region: Visible	Near IR	Middle IR	Thermal IR
1	44.0%	1.5-1.8			1	
2	80.5%	1.5-1.8, 0.58-0.65	1		1	
3	87.1%	1.5-1.8, 0.58-0.65, 9.3-11.7	1		1	1
4	89.3%	1.5-1.8, 0.58-0.65, 9.3-11.7, 0.52-0.57	2		1	1
5	90.8%	1.5-1.8, 0.58-0.65, 9.3-11.7, 0.52-0.57, 1.0-1.4	2	1	1	1
6	92.4%	1.5-1.8, 0.58-0.65, 9.3-11.7, 0.52-0.57, 1.0-1.4, 2.0-2.6	2	1	2	1
8	93.7%	1.5-1.8, 0.58-0.65, 9.3-11.7, 0.52-0.57, 1.0-1.4, 2.0-2.6, 0.61-0.70, 0.72-0.92	3	2	2	1
10	94.7%	1.5-1.8, 0.58-0.65, 9.3-11.7, 0.52-0.57, 1.0-1.4, 2.0-2.6, 0.61-0.70, 0.72-0.92, 0.46-0.49, 0.50-0.54	5	2	2	1
12	95.1%	1.5-1.8, 0.58-0.65, 9.3-11.7, 0.52-0.57, 1.0-1.4, 2.0-2.6, 0.61-0.70, 0.72-0.92, 0.46-0.49, 0.50-0.54, 0.48-0.51, 0.54-0.60	7	2	2	1

[1]From Coggeshall and Hoffer (1973).

[2]Based on 6 classes, involving 49,794 resolution elements in 158 test areas.

[3]Wavelength band selection sequence defined by the "Feature Selection Processor" in the LARSYS software.

Table 2. Wavelength Band Selection Sequence and Classification Results For Major Cover Types Using Skylab Data[1]

No. of Channels Used	Test Area Classification Results[2]	Wavelength Bands Selected[3]	Number of Bands in Each Major Wavelength Region			
			Visible	Near IR	Middle IR	Thermal IR
1	75.7%	1.09-1.19		1		
2	76.8%	1.09-1.19, 0.46-0.51	1	1		
3	81.9%	1.09-1.19, 0.46-0.51, 0.78-0.88	1	2		
4	85.0%	1.09-1.19, 0.46-0.51, 0.78-0.88, 1.55-1.75	1	2	1	
5	84.1%	1.09-1.19, 0.46-0.51, 0.78-0.88, 1.55-1.75, 0.56-0.61	2	2	1	
6	83.7%	1.09-1.19, 0.46-0.51, 0.78-0.88, 1.55-1.75, 0.56-0.61, 10.2-12.5	2	2	1	1
7	85.3%	1.09-1.19, 0.46-0.51, 0.78-0.88, 1.55-1.75, 0.56-0.61, 10.2-12.5, 2.10-2.35	2	2	2	1
8	84.1%	1.09-1.19, 0.46-0.51, 0.78-0.88, 1.55-1.75, 0.56-0.61, 10.2-12.5, 2.10-2.35, 0.41-0.46	3	2	2	1
10	85.2%	1.09-1.19, 0.46-0.51, 0.78-0.88, 1.55-1.75, 0.56-0.61, 10.2-12.5, 2.10-2.35, 0.41-0.46, 0.98-1.08, 1.20-1.30	5	5	2	1
13	86.0%	1.09-1.19, 0.46-0.51, 0.78-0.88, 1.55-1.75, 0.56-0.61, 10.2-12.5, 2.10-2.35, 0.41-0.46, 0.98-1.08, 1.20-1.30, 0.52-0.56, 0.62-0.67, 0.68-0.76				

[1]From Hoffer et al. (1975).

[2]Based on 6 classes, involving   resolution elements in   test areas.

[3]Wavelength bands selection sequence defined by the "Feature Selection Processor" in the LARSYS software.

IV. THE "MYSTERY" OF "WHICH CLASSIFICATION TECHNIQUE IS THE BEST ONE?"

A. Training Versus Classification

Computer classification of MSS data involves a series of steps designed to enable the computer to identify and map various cover types or earth surface features of interest. The key elements in this process involve the development of a set of "training statistics" (which represent the spectral reflectance of the various features or cover types of interest), and then the actual classification of the MSS reflectance values for each resolution element (or a subset thereof) by the computer.

There has been a tendency among remote sensing researchers to assume that the accuracy of computer classification results is primarily a function of the algorithm used in the classification process. Much attention has been given to the various classification algorithms, but relatively little emphasis has been given to the procedures used to develop the training statistics. It is my belief that the process involved in developing the training statistics is very critical, and indeed is the key to effective use of the computer for mapping vegetative cover using satellite MSS data! Therefore, questions concerning the "best" classification techniques really should address both (1) the method used to define the training statistics and (2) the effectiveness of the classification algorithm itself.

B. Comparisons Among Techniques for Defining Training Statistics

Several methods to defining a set of training statistics have been developed. Among the more common are the following:

(1) The "Supervised Training Field" technique, in which the analyst designates to the computer the X-Y coordinates of training fields of the various cover types of interest.

(2) The "Clustering" or "Non-supervised" technique, in which the analyst simply designates the area to be classified and a specified set of analysis parameters (such as the number of spectral classes to be defined).

(3) The "Multi-Cluster Blocks" technique, which is a hybrid of the above two techniques (Fleming and Hoffer, 1977). In this approach the analyst locates several relatively small blocks in the data, each of which contains several cover types and spectral classes. Each data block is individually clustered, and then the spectral classes for all cluster areas are combined, through a series of man/machine interactions, to form a single data deck of training statistics.

(4) The "Procedure-1" technique (developed at NASA's Johnson Space Center during the LACIE program), in which an array of individual resolution elements of known cover type are used to "seed" a

clustering processor, which then defines the training statistics for the various cover types.

Results obtained with the various training techniques vary. The "Supervised Training Field" technique is the most easily understood and has probably been the most frequently used approach. This technique has been used very effectively for agricultural mapping (Bauer, 1975), and several forestry applications studies have utilized this technique, but with varying degrees of success (Dodge and Bryant, 1976; Williams and Haver, 1976; Mead and Meyer, 1977). Our own experience at Purdue has shown that for wildland forested areas, where the cover types of interest are often spectrally and spatially complex, this supervised technique frequently does not allow an acceptable level of accuracy or reliability to be obtained. The primary reason for this is the difficulty the analyst has in defining locations in the data that represent all significant variations in spectral response for every cover type of interest.

The "Clustering" technique effectively overcomes the primary limitation of the "supervised" approach, since every pixel in the area of interest is included in the process of developing the training statistics. However, when working with large areas, a very large amount of computer time is often required for the iterative clustering sequence, thereby making this technique very expensive. For this reason, it has not been utilized on forestry studies involving relatively large geographic areas.

The "Multi-Cluster Blocks" technique overcomes the major limitations of both the Supervised and Clustering approaches by clustering heterogeneous blocks of data but restricting the size of the areas being clustered in order to minimize computer costs. Usually, less than one percent of the entire area of interest is involved in the development of the training statistics. By clustering relatively small blocks, the analyst can effectively relate the cluster classes defined by the computer to the cover types and characteristics seen on an aerial photo of the clustered areas.

In addition to the Multi-Cluster Block technique (as defined by Fleming and Hoffer, 1977), there are several other procedures whereby the analyst can combine various features of the supervised and non-supervised techniques. These can all be considered as "hybrid clustering" techniques, and include: (1) combining several heterogeneous blocks and then clustering the entire group as a single unit (e.g., "Mono-Cluster Blocks"); (2) grouping supervised training fields into a single block and clustering this block (e.g., "Mono-Cluster Fields"); and (3) clustering supervised training fields individually and then combining the statistics into a single data deck (e.g., "Multi-Cluster Fields").

To evaluate the importance of the method used, a quantitative comparison was made by Fleming and Hoffer (1977) among six different techniques for developing training statistics. After the training statistics were developed, the same set of data was classified using a maximum likelihood classifier, and the same test areas were used for the comparison. These results, shown in Table 3, indicate that the method of developing training statistics can have a statistically significant impact on:

Table 3. A comparison of six techniques for developing training statistics.

Technique Used	Analyst Time Required (Hours)	Computer Time Used (C.P.U. Minutes)	Estimated Cost Per 1000 Hectares 1/	Resultant Classification Performance 2/
Supervised	53	25.2	$1.18	64.7%
Non-Supervised Cluster	26	48.4	$0.85	76.9%
Multi-Cluster Blocks	12	21.8	$0.39	78.8%
Mono-Cluster Blocks	10.5	25.1	$0.39	73.1%
Multi-Cluster Fields	50	19.3	$1.07	69.7%
Mono-Cluster Fields	46.5	22.4	$1.03	69.4%

[1] Costs include only the analyst and C.P.U. time required to develop the training statistics for a relatively large study site (i.e., 540,580 hectares or 1,335,797 acres). Costs were calculated on the basis of $250/C.P.U. hour plus $10/man-hour.

[2] Based upon a statistically defined grid of test fields which were classified using a maximum likelihood algorithm.

(a) the accuracy of classification achieved;

(b) analyst time required for developing the training statistics;

(c) computer time required; and

(d) ease and effectiveness of the analyst/data interface

Of particular interest was the finding that the "Supervised" technique resulted in the lowest classification accuracy, as well as requiring the largest amount of computer CPU time!

This study concluded that for areas of complex vegetative cover, the "Multi-Cluster Blocks" was the most effective technique for developing training statistics. This technique is believed to be particularly useful in situations where little reference data exists. In such cases, a sample of medium-scale aerial photography can be obtained and used to identify the informational classes within cluster blocks.

In many situations, however, reference data does exist, and it is desirable to make use of such data if possible. "Procedure-1" is a relatively new method for developing training statistics that was developed at NASA's Johnson Space Center, Houston, Texas, during the LACIE (Large Area Crop Inventory Experiment) project. The Procedure-1 (or P-1) technique involves use of a set of small points of known cover type. Although developed for agricultural applications, it would appear that such a technique could also be used for mapping forest cover in situations where a grid of samples of known cover type exists (such as the U.S.F.S. Forest Survey samples or the Washington state GRIDS data).

A recent comparison between the P-1 method of developing training statistics and the Multi-Cluster Blocks approach resulted in classifications that had no statistically significant difference (Nelson and Hoffer, 1979). This study concluded that the P-1 technique has considerable potential for developing training statistics in situations where a grid sample of points of known cover type exists. However, where such a data set is not already in existence, the Multi-Cluster Blocks would be the most effective technique.

In summary, it would appear that (a) the technique used to develop the training statistics can have a significant impact on the results obtained, and (b) the availability and type of reference data may dictate which technique for developing training statistics would be most efficient and effective in a given situation.

C. Comparisons Among Classification Algorithms

It is apparent from the above discussion that the method used to develop training statistics can have a significant impact on the results. But what about the effect of the classification algorithm?

There are many algorithms available to the analyst, of which the maximum likelihood per point classifier is one of the most powerful and widely-used. Results of three recent studies tend to indicate that if an effective set of training statistics have been developed, the classification algorithm used does not affect the accuracy of the classification results as much as had been expected. In each of these studies, a single set of training statistics were used for the classifications. A series of classifications were run, each of which involved a different classification algorithm. The same set of test fields were then used to evaluate the results of each of the classifications.

The first study involved a comparison between four different algorithms on a mountainous, forested test site in southwestern Colorado (Bauer, et al., 1977). Based upon classifications of Level II cover types (Anderson et al., 1976), as well as Level III or individual forest cover types, the results showed that approximately the same classification accuracy was achieved with each of the algorithms tested — Maximum Likelihood Per Point, ECHO, Layered, and Minimum Distance to the Means — as shown in Table 4. However, as is also indicated in this table, the cost involved in classifying the data can vary significantly, depending on the algorithm used.

Results of another study in the same test site indicated no statistically significant difference between the Maximum Likelihood Per Point and the Sum of Normal Densities algorithms when they were applied to the identification and mapping of both (a) major cover types (Level II) and (b) individual forest cover types (Level III) (Nelson and Hoffer, 1979).

The third study involved agricultural crops in three different data sets, and compared the Maximum Likelihood Per Point, ECHO, Layered, Minimum Distance to the Means, and Sum of Normal Densities classification algorithms. Once again, these results showed no statistically significant difference in classification accuracy among the algorithms compared (Scholz et al., 1979).

The results of these three studies tend to indicate that the particular classification algorithm used may not be as important as had been previously thought! However, this possibility needs to be further tested on a variety of data sets.

The primary point that should be stressed in discussing computer classification of MSS data, is that no matter which classification algorithm is utilized, the <u>training statistics must effectively represent the spectral characteristics of the various cover types present in that data set</u>! If the training statistics are not representative, the classification results will not be satisfactory, no matter which classification algorithm is utilized (i.e., garbage in = garbage out)!

D. Alternatives to "Per Point" Classifiers

In considering which classification algorithm is "best", one should consider more than just the classification performance based on test data sets. The qualitative characteristics of the classification output should also be evaluated. For example, most classification algorithms classify each resolution element in the data individually. This often results in a "salt-and-pepper" effect in the classification map obtained. Users often object to such a product because it is too "busy" and contains more detail than is actually desired. To overcome this objection, computer programs have been developed to post-process the classification results and "smooth" them to

Table 4. A comparison of four classification algorithms.

Algorithms Used	Analyst Time[1] Required (Hours)	Computer Time[2] Used (C.P.U. Minutes)	Estimated Cost[3] Per 1000 Hectares	Classification[4] Performance Level II	Level III
Maximum Likelihood Per Point	0.17	7.5	$2.15	93.8%	75.0%
ECHO	0.25	4.5	$1.38	92.8%	73.0%
Layered	0.5	4.3	$1.50	92.8%	74.5%
Minimum Distance to the Means	0.17	2.8	$0.87	93.5%	75.9%

[1]Time (cost) for developing training statistics not included.

[2]Based upon classification of every Landsat resolution element in one USGS 7½' quadrangle (15,303 hectares or 37,190 acres).

[3]Calculated on the basis of $250/C.P.U. hour plus $10/man-hour.

[4]Based upon evaluation of test areas which were field checked and included 3.704 acres (10% sample).

Level II = Coniferous forest, Deciduous forest, Grassland, Barren, and Water.

Level III = Ponderosa pine, Spruce/fir (< 80% crown closure); Spruce/fir (> 80% crown closure), Mixed coniferous/deciduous, Aspen, Oak, Rangeland, Agricultural land, Barren and Water.

eliminate much of the salt-and-pepper effect.

Another approach to providing the user with a more useful result involves techniques that utilize the spatial variability in the spectral data to do the initial classification. One such classification algorithm is referred to as the "ECHO" (Extraction and Classification on Homogeneous Objects) classifier (Kettig and Landgrebe, 1976). In essence, this algorithm incorporates what a photo interpreter would call "texture" into the classification. In this technique, the computer is programmed to define the boundary around an area having generally similar spectral characteristics, and then the entire area within the boundary is classified as a single spectral class. A key aspect to this algorithm is that the boundaries of the forest stand or agricultural field are defined by the computer. This results in an output map that has an appearance somewhat like a standard forest type map obtained by manual photo interpretation. In evaluating this type of classification map, some users expressed a strong preference for the ECHO map output, whereas others, who were involved with different applications, preferred the "per point" classification output maps. It seems clear that different algorithms having different characteristics must be available to be used as appropriate in meeting a variety of user needs! <u>There probably is no single "magical" classification algorithm that will be completely satisfactory for all user needs!</u>

In considering different users and their particular information needs, we should not assume that it is always necessary to apply a <u>classification</u> algorithm to MSS data in order to produce the most useful output. An interesting study by Kourtz and Scott (1978) involved the generation of forest fire fuel maps using Landsat data and computer analysis techniques. It was found that neither supervised or unsupervised classifications were satisfactory because these techniques grouped the data into a relatively few, well-defined categories, and important transition areas did not show. However, by using some rather sophisticated computer enhancement procedures, output imagery was produced which showed key features of interest and which was much more satisfactory to the field personnel (i.e., the <u>real</u> "users"). Kourtz and Scott point out that:

> "Psychologically keeping the field personnel involved in the interpretation process appears to be essential for this application."

This comment points out the necessity of working closely with users, and to carefully evaluate their requirements in order to provide them with the type of product that is most useful for meeting <u>their</u> particular needs. We should also remember that Landsat data and computer processing techniques are not appropriate for many applications, and it does more harm than good to "oversell" the capabilities that such data and analysis techniques do have, or try to force them upon users in inappropriate situations.

V. WHAT ARE THE EXISTING CAPABILITIES?

During the past decade there have been a number of studies involving MSS data and computer analysis techniques which have been directed at identifying and mapping forested areas and individual forest species. What have we learned? What can be done with these instruments and techniques?

In examining the literature, it is clear that (a) the technology is far from "standardized", and (b) the spectral, spatial, and temporal characteristics of the forest scene are complex. A majority of the studies to date have involved relatively limited test sites, so it becomes difficult to reliably extrapolate the results to larger geographic areas. In some cases, the areas studied may not even be particularly typical of the region or the characteristics of the various cover types. Different study objectives, a variety of software and hardware, different analysis techniques, and diverse levels of analyst experience all contribute to the difficulty in attempting to assess the true capabilities and limitations of this technology. Perhaps one of the most difficult aspects of such an attempt involves the fact that different researchers use widely different approaches to evaluate their results. In some cases, the results have been evaluated qualitatively by visually comparing the classification to an existing cover type map or to aerial photos of the region. Although the method is subjective, it does provide a quick, rough estimate of the accuracy of the classification. More definitive evaluations of the computer classification results can be obtained by more quantitative techniques.

One quantitative evaluation technique involves a sample of individual areas of known cover types which are designated as "test areas." The cover types into which the test areas were classified are tabulated by the computer and these results are then compared to the cover types actually present on the ground. Definition of a statistically sound set of test data is not an easy task however. Arbitrary selection of test areas often results in definition of a test data set that is very typical, and consequently the results tend to be biased. Some studies have even used the training data to evaluate the classification! Such an approach is not valid, however, since accurate classification of the training data merely indicates the spectral separability of the various cover types. The training data sometimes is not an accurate representation of the spectral characteristics of the study area, in which case the classification will be somewhat inaccurate regardless of how accurately the training data is classified. To effectively and reliably evaluate the classification results, a statistically defined set of test data should be used.

In addition to the use of test areas to evaluate the classification results, another quantitative technique involves a comparison of acreage estimates obtained from the computer classification of satellite data to estimates obtained by some conventional method, such as manual interpretation of aerial photos or statistical summaries such as obtained by the USFS Forest Survey.

In considering the results obtained by computer classification of MSS data, we should also remember that the characteristics and quality of the reference data can influence the evaluation of classification results. The definition of what constitutes forest land, for example, can influence the decision as to whether a particular location in the data was classified by the computer correctly or incorrectly. In addition, the computer classification results are frequently compared to data obtained through manual interpretation of aerial photos. Since photo interpretation (or most any other method of defining ground "truth") is not always 100% accurate, it is possible that a certain amount of error may be involved in the evaluation of the classification results due to identification errors in the reference data.

So where do we stand in terms of the capability to identify and map forestland and individual forest species using MSS data and computer-aided analysis techniques? In general, it would appear from the literature that major categories of land cover, such as forested areas, rangeland, and agricultural land can be identified and mapped with a fairly high degree of accuracy and reliability, generally 80-95% (Heller, 1975; Hoffer, 1975 a & b, 1978a; Kalensky, 1975; Dodge, 1976; Schecter, 1976; Williams, 1976; Odenyo, 1977; Miller, 1978; NASA, 1978). Estimates of total forest acreage using Landsat data and computer classification techniques were generally within $\pm$ 10% of those obtained by U.S. Forest Service Forest Survey (Dodge, 1976; Aldrich, 1979). In one study, the forest acreage estimate for a nine-county area in Virginia that was less than 1% different from the Forest Survey estimate (Roberts, 1979), and another study reported that estimates of forest acreage for the entire State of Michigan obtained by classification of Landsat data were within 2% of those obtained by the U.S. Forest Service (Hoffer, et al., 1978c). Thus, it would appear that quite accurate acreage estimates of forestland can be achieved, at least over reasonably large areas. Such estimates were less accurate on smaller areas in each of the last two studies cited.

In addition to being able to identify forested versus non-forested areas quite accurately, the literature cited above indicates that the capability to differentiate between deciduous and coniferous cover types seems to be rather good (e.g., 70-90%) unless they occur in mixed stands. In mixed stands, the spatial characteristics of the Landsat scanner system result in a spectral response that is approximately proportional to the relative percentage of cover types present, but is also influenced by variations in stand density (Kan, 1975; Dodge, 1976; Williams, 1976; Hoffer, 1978a). Identification and mapping of individual forest species generally has been significantly less accurate, with results varying considerably, ranging from 50 or 60% to perhaps 70 or 80% in some cases. In some studies conducted with Landsat data, the accuracy was very low for various individual species (NASA, 1978; Hoffer, 1975a & b, 1978a). However, a study by Rhode and Olson (1972) using aircraft data having better spectral characteristics than Landsat provides indicated that perhaps certain species or groups of species can be accurately differentiated and identified, at least if they are found in pure stands. Spectral similarity among species often causes confusion between individual species within the deciduous or coniferous category. Variations in stand density as well as topographic effects cause significant differences in spectral response, thereby resulting in additional difficulties in being able to obtain highly accurate species differentiation (Hoffer, 1975a & b; Williams, 1976).

VI. WHERE DO WE GO FROM HERE?

Since the launch of Landsat-1 in 1972, there has been rapid progress in developing computer-aided analysis techniques and in understanding how to effectively use such techniques. Many of the limitations as well as the capabilities of the Landsat MSS type of data are now understood reasonably well. In the years ahead, it is anticipated that the spectral and spatial characteristics of the Thematic Mapper scanner system (to be launched on Landsat-D in 1981) will allow significant improvements to be realized in the capability to map forest cover types using computer analysis techniques. The Thematic Mapper will obtain data in seven relatively narrow wavelength bands and will have 30 meter spatial resolution, as compared to the four relatively broad bands and 80 meter resolution of the MSS systems on Landsats 1, 2, and 3. Table 5 shows a comparison between the current Landsat scanner systems and the Landsat-D Thematic Mapper system.

It is becoming more and more apparent that for some applications, the spectral data obtained by satellite MSS systems should be supplemented with data from other sources in order to improve the computer classification results. For example, the use of soils data in conjunction with Landsat MSS data enables upland hardwood to be separated from swamp hardwoods more reliably than can be done using Landsat data alone. Likewise, the combination of soils and Landsat data allow areas of wetlands to be identified more reliably than is possible using only Landsat data (Ernst and Hoffer, 1979). Another recently completed study in the Rocky Mountains of Colorado involved use of topographic data (elevation, aspect, and slope) in conjunction with Landsat MSS data to map individual forest cover types. The results indicated that, as compared to using Landsat data alone, a 15% improvement in classification of forest cover types was achieved through use of the combined Landsat plus elevation data (Fleming and Hoffer, 1979).

The combination of satellite MSS data and soils, topographic or other data types into digital data bases, along with existing and developing computer processing capabilities offers a tremendous potential for providing resource managers with timely, accurate, and reliable data in the most useable format. Different analysis techniques will have to be developed, however, to handle the different types of data in ways that are both theoretically sound and operationally feasible. Much work also remains to be done in defining effective digital processing techniques for analyzing Synthetic Aperture Radar (SAR) data. The 25-meter resolution X-Band SAR data obtained by the Seasat satellite has indicated an excellent potential for satellite-borne SAR data collection systems. The value of such data, particularly when used in conjunction with MSS and ancillary data, would seem to offer tremendous possibilities for resource assessment in the years ahead.

This past decade has witnessed tremendous developments in remote sensing data collection and analysis techniques. As new and more sophisticated instrumentation and data processing capabilities are developed, we must continue to realistically assess the potentials and limitations of these capabilities. If the natural resources of the world are to be managed effectively and efficiently, it is vital to have accurate, reliable, and timely information concerning

Table 5. Comparison of spectral and spatial characteristics of the MSS on Landsats 1, 2, and 3 and the Thematic Mapper Scanner on Landsat D.

Spectral Region	MSS (Landsats 1, 2, & 3)[1]		Thematic Mapper (Landsat D)	
	Bandwidth (m)	Spatial Resolution (m)	Bandwidth (m)	Spatial Resolution (m)
Visible	0.5-0.6	80	0.45-0.52	30
	0.6-0.7	80	0.52-0.60	30
			0.63-0.69	30
Near IR	0.7-0.8	80	0.76-0.90	30
	0.8-1.1	80		
Middle IR	-		1.55-1.75	30
			2.08-2.35	30
Thermal IR	-		10.4-12.5	120

[1] Landsat 3 had a thermal infrared band, but it did not function properly and was turned off.

the various resources of concern. It seems clear that remote sensing and computer-aided analysis techniques are starting to and will continue to play a significant role in providing this information.

REFERENCES

Aldrich, R. C. 1979. "Remote sensing of wildland resources; a state-of-the-art review, 1978." U.S. Forest Service Report, Ft. Collins, Colorado. 131 pp.

Anderson, J. R., E. E. Hardy, J. T. Roach, and R. E. Witmer. 1976. A land use and land cover classification system for use with remote sensor data. Geological Survey Professional Paper 964. U.S. Geological Survey, Washington, D.C. 28 pp.

Bauer, M. E. 1975. "The role of remote sensing in determining the distribution and yield of crops." Advances in Agronomy 27:271-304.

Bauer, M. E., L. F. Silva, R. M. Hoffer, and M. F. Baumgardner. 1977. "Agricultural scone understanding." LARS Contract Report 112677. Laboratory for Applications of Remote Sensing, Purdue University, West Lafayette, Indiana. pp. 61-65.

Dodge, A. G., Jr., and E. S. Bryant. 1976. "Forest type mapping with satellite data." Journal of Forestry 74(8):526-531.

Ernst, C. L., and R. M. Hoffer. 1979. "Using Landsat MSS data with soils information to identify wetland habitats." Proceedings of the International Symposium on Satellite Hydrology, Sioux Falls, South Dakota. 18 pp.

Fleming, M. D., and R. M. Hoffer. 1977. "Computer-aided analysis techniques for an operational system to map forest lands utilizing Lnadsat MSS data." LARS Technical Report 112277. Purdue University, West Lafayette, Indiana. 236 pp.

Fleming, M. D. and R. M. Hoffer. 1979. "Machine processing of Landsat MSS data and DMA topographic data for forest cover type mapping." Proceedings of the 1979 Symposium on Machine Processing of Remotely Sensed Data, Purdue University, West Lafayette, Indiana. pp 377-390.

Heller, R. C., Technical Coordinator. 1975. "Evaluation of ERTS-1 data for forest and range-land survey." USDA Forest Service Research Paper PSW-112, Pacific S.W. Forest and Range Experiment Station, Berkeley, California. 67 pp.

Hoffer, R. M. and C. J. Johannsen. 1969. "Ecological potentials in spectral signature analysis." Chapter 1 in: Remote Sensing in Ecology, P. Johnson, ed., University of Georgia Press, Athens, Georgia. pp. 1-16.

Hoffer, R. M. and Staff. 1975a. "Natural resource mapping in mountainous terrain by computer analysis of ERTS-1 satellite data." Agricultural Experiment Station Research Bulletin 919, Purdue University, West Lafayette, Indiana. 124 pp.

Hoffer, R. M. 1975b. "Computer-aided analysis of Skylab scanner data for land use mapping, forestry and water resource applications." Proceedings of the Eleventh International Symposium on Space Technology and Science, Tokyo, Japan. pp. 935-941.

Hoffer, R. M., and M. D. Fleming. 1978a. "Mapping vegetative cover by computer-aided analysis of satellite data." Proceedings of the Workshop on Integrated Inventories of Renewable Natural Resources, General Technical Report RM-55, Rocky Mountain Forest and Range Experiment Station, U.S. Forest Service, Ft. Collins, Colorado. pp. 227-237.

Hoffer, R. M. 1978b. "Biological and physical considerations in applying computer-aided analysis techniques to remote sensor data." Chapter 5 in: Remote Sensing: The Quantitative Approach, P. H. Swain and S. M. Davis, eds. pp. 227-289.

Hoffer, R. M., S. C. Noyer, and R. P. Mroczynski. 1978c. "A comparison of Landsat and forest survey estimates of forest cover." Proceedings of the Fall Technical Meeting of the American Society of Photogrammetry. pp. 221-231.

Kalensky, Z., and L. R. Scherk. 1975. "Accuracy of forest mapping from Landsat computer compatible tapes." Proceedings of the Tenth International Symposium on Remote Sensing of Environment. Ann Arbor, Michigan. 9 pp.

Kan, E. P., D. L. Ball, J. P. Basu, and R. L. Smelser. 1975. "Data resolution versus forestry classification and modeling." Proceedings of the 1975 Symposium on Machine Processing of Remotely Sensed Data. Purdue University, West Lafayette, Indiana. pp. 1B-24 to 37.

Kettig, R. L. and D. A. Landgrebe. 1976. "Classification of multispectral image data by extraction and classification of homogeneous objects." IEEE Trans. Geos. Elect. 14:19-25.

Kourtz, P. H. and A. J. Scott. 1978. "An improved image enhancement technique and its application to forest fire management." Proceedings of the Fifth Canadian Symposium for Remote Sensing. Victoria, B.C. 9 pp.

Mead, R., and M. Meyer. 1977. "Landsat digital data application to forest vegetation and land-use classification in Minnesota." IAFHE RSL Research Report 77-6. University of Minnesota, St. Paul, Minnesota. 57 pp.

Miller, L. D. and L. L. Williams. 1978. "Monitoring forest canopy alteration around the world with digital analysis of Landsat imagery." From Proceedings ISP/IUFRO International Symposium on Remote Sensing Observation and Inventory of Earth Resources and Endangered Environment, Freiburg, Germany. 41 pp.

NASA. 1978. Skylab EREP investigations summary. NASA SP-399. National Aeronautics and Space Administration, Johnson Space Center, Houston, Texas. 386 pp.

Nelson, R. F. and R. M. Hoffer. 1979. "Computer-aided processing of Landsat MSS data for classification of forestlands." LARS Technical Report 102679. Purdue University, West Lafayette, Indiana. 95 pp.

Odenyo, V. A. O. and D. E. Pettry. 1977. "Land use mapping by machine processing of Landsat-1 data." Photogrammetric Engineering and Remote Sensing 43(4):515-524.

Roberts. E. H. and N. E. Merritt. 1977. "Computer-aided inventory of forestland." Type III Final Report, USDA Forest Service, Rocky Mountain Forest and Range Experiment Station, Ft. Collins, Colorado. pp. 65-74.

Rhode, W. G. and C. E. Olson. 1972. "Multispectral sensing of forest tree species." Photogrammetric Engineering 38(12):1209-1215.

Schecter, R. N. 1976. "Resource inventory using Landsat data for areawide water quality planning." Proceedings of the 1976 Symposium on Machine Processing of Remotely Sensed Data. Purdue University, West Lafayette, Indiana. pp. 1B-1 to 10.

Scholz, D., N. Fuhs, and M. Hixson. 1979. "An evaluation of several different classification schemes: their parameters and performance." Proceedings of the Thirteenth International Symposium on Remote Sensing of the Environment. Ann Arbor, Michigan. 7 pp.

Williams, D. L. and G. F. Haver. 1976. "Forest land management by satellite: Landsat derived information as input to a forest inventory system." NASA/Goddard Space Flight Center, Greenbelt, Maryland. 36 pp.