# Pecora 10

REMOTE SENSING IN
FOREST AND RANGE RESOURCE MANAGEMENT

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# EVALUATION OF A LAYERED APPROACH FOR CLASSIFYING MULTITEMPORAL LANDSAT MSS DATA

D. Fabian Lozano-Garcia and Roger M. Hoffer
Department of Forestry and Natural Resources
Purdue University
West Lafayette, Indiana 47907

## ABSTRACT

Two different methods for analysis of multitemporal MSS data were compared in this study. The first involved the use of a single stage maximum likelihood classifier. The second approach made use of a hierarchical classifier (Layered classifier) which consist of a sequence of classification steps, each of which can incorporate a different wavelength band or combination of wavelength bands. In addition, at each step in the classification process, only one spectral class or group of classes are separated from all other classes in the data. Thus, the classification procedure is more efficient since only a relatively small number of wavelength bands and a small portion of the data is involved in each decision step.

Landsat-1 MSS data were obtained over the Hoosier National Forest in June 1973 and February 1974. After performing a digital registration of these two data sets, a series of four specific classifications were compared. The first consisted of a standard single stage maximum likelihood classification using an eight channel training statistics deck. The second utilized the four best channels of the eight available, using a single stage maximum likelihood classifier. The third classification involved the Layered classifier and the same eight channel training statistics. In the fourth approach each of the two dates were used independently to develop two sets of training statistics which were then used as input for the Layered classifier algorithm.

The results indicate that the Layered classifier is a more effective and efficient approach for the analysis of multitemporal data sets. The classification accuracies were relatively high for all four classifications but the Layered classifier required only one third of the CPU time used in the single stage classifications.

## INTRODUCTION

Classification of multispectral scanner data has been performed traditionally with single stage classification algorithms. One characteristic of these algorithms is that they involve the categorization of the data using only one of the many available sets of spectral channels; (usually all the available channels are used). The large number of computations required and the sensitivity of the classification algorithm to category variance are the primary limitations of the single-stage techniques.

For some remote sensing applications, a classification technique based on the layered or decision tree approach can be utilized. In this method, the multispectral scanner data is classified through a hierarchical decision procedure (Figure 1) in which the analyst goes through a series of decision nodes, and at each node he/she selects the best set of spectral channels that separate a class or group of classes from certain other cover types. This separation is made step by step, until all classes have been separated. The actual classification of each pixel is performed using any of the available per-point algorithms.

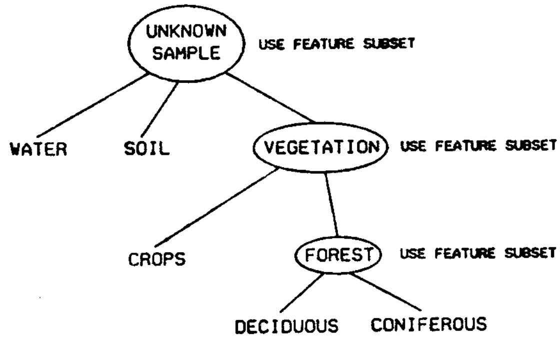


FIGURE 1. HYPOTETICAL HIERARCHICAL DECISION TREE.

Two of the major limitations of the single stage classifiers (that are not present in the Layered classifier) are:

1) Only one of the many possible combinations of wavebands (features) is used in the single stage classification. However, there may be some subsets which are more effective than the entire set of channels, or some subsets may be more effective for the discrimination of a particular spectral class.

2) In the standard single stage classification, every data sample is tested against all classes. This characteristic leads to very low efficiency.

Hierarchical classifications have not been used commonly in the analysis of remotely sensed data. One of the earliest applications of this scheme was the work of Bartolucci et al. (1973) in mapping water temperatures. The authors used this approach to separate water from all other cover types in the first stage of the decision tree, using the best set of channels to accomplish this separation. The second step was to classify the water temperatures using the available thermal channel. They found this approach to be superior to the use of the single stage classification procedure. Hoffer et al. (1979) used the Layered classifier in a study of combined multispectral scanner and digital topographic data. Their approach was to separate cover types using the spectral data in the first stage. The next stage of the classification involved the utilization of topographic data to divide the major cover types into individual forest cover types, and to remove some misclassification errors due to shadow effects. The results showed an improvement of approximately sixteen percent as compared to the use of spectral data alone using a single stage classification.

The Layered classifier has been applied to a multitemporal data set by Landgrebe (1976), who classified a set of agricultural areas. Weismiller et al. (1977) also utilized this technique in a change detection procedure. Hixson et al. (1980) compared this classifier against six others. In general, their conclusions indicate that the time required by the analyst to design the decision tree can be significant. Also, they concluded that the Layered classifier is well suited to handle multitemporal MSS data sets.

## STUDY AREA

The study area is located in the Hoosier National Forest and the Brown County State Forest, south-east of Bloomington, Indiana. The forest of the area is classified according to Petty and Jackson (1966) as:

WESTERN MESOPHYTIC ASSOCIATION.-- In this community, ten to twenty species frequently share dominance in the crown cover and exert their controlling influence on the forest community. The mixed forest usually occurs in ravines and on the cooler slopes, whereas oak or oak-hickory forests cover the drier slopes and ridges.

OAK-HICKORY ASSOCIATION (Quercus-Carya).-- The oak-hickory forests are usually found occupying south-facing and west-facing slopes. In general, moisture content of the soil is consistently lower than in the oak-hickory type than the mesophytic mixed forest.

The study area is largely forested, mostly by tulip poplar, oak, maple, hickory, ash, walnut and sycamore. Small stands of pine are scattered in the study area. The steep slopes and heavily dissected topography have discouraged the extensive clearing of this area for agriculture, although selective logging has altered the composition of most stands. On the valley bottoms in the western, south-western and east central portion of the area the forest has been substituted for crops and pasture. Some portions of suburban Bloomington occur in the north-western corner of the area. Monroe Reservoir, Lemon Lake, Yellowood Lake and Grandview Lake are the major water bodies in the area.

## AVAILABLE DATA

Seven dates of registered multispectral scanner images of the Landsat-1 satellite (Table 1) were available for a portion of the Hoosier National Forest including Monroe Reservoir and the surrounding areas. The data sets from June 1973 and February 1974 were selected due to their high quality, minimum cloud cover, and available ground reference data.

Table 1. Available Landsat MSS data sets.

| Scene ID | Date | Season |
|---|---|---|
| 1285-16001 | May 4, 1973 | Spring |
| 1320-15541 | June 8, 1973 | Late spring |
| 1392-15531 | August 19, 1973 | Summer |
| 1411-15584 | September 7, 1973 | Late summer |
| 1482-15514 | November 17, 1973 | Late fall |
| 1572-15493 | February 15, 1974 | Winter |
| 1591-15550 | March 8, 1974 | Late winter |

## ANALYSIS PROCEDURES USED

Table 2 shows the four different classification techniques utilized in this work. They can be divided into single stage and Layered classifiers. In the single stage approach two methods were tested -- one with all eight channels and the other with the four best channels. The Layered approach was first tested using the same training statistics generated for the eight channel, single stage approach. The second layered classification involved generating two sets of independent training statistics -- one for each date.

Table 2. Characteristics of classifications being compared.

| | Classification Number | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Classification Technique | Single Stage | Single Stage | Layered Stage | Layered Stage |
| Statistics used for training | All $8\lambda$ | "Best" $4\lambda$ | Combined Dates (All $8\lambda$) | Separate Dates ($4\lambda$ for June; $4\lambda$ for Feb.) |
| Algorithm used for classification | GML | GML | GML | GML |

<u>Multitemporal/Multispectral Single Stage Classifications</u>

The first analysis conducted in this study involved classifications of a two date, eight channel data set. The dates selected were June of 1973 and February of 1974.

Training statistics were generated using a "multi-cluster blocks" approach, similar to the one described by Fleming et al. (1975).

Two different classifications were performed with this data set. The first used all the channels of both dates -- Multitemporal/Multispectral 8 channels (Figure 2). In the second classification, four channels were selected based upon the minimum and average transformed divergence value (Figure 3). The selected channels were:

Table 3. Selected wavebands for the single-stage four wavebands classification.

| Waveband | Date | Spectral Region |
|---|---|---|
| 0.6-0.7 μm | June | Visible (red) |
| 0.7-0.8 μm | June | Reflective IR |
| 0.6-0.7 μm | February | Visible (red) |
| 0.7-0.8 μm | February | Reflective IR |

It is important to point out that the analysis sequence resulted in one channel in each major portion of the spectrum (i.e., visible and reflective infrared) covered by Landsat-MSS was selected for this classification.

<u>Layered Classifications</u>

One of the characteristics of the layered classifier is that it permits the analyst to optimize the use of certain spectral bands in the separation of a class or group of classes. In a multitemporal/multispectral classification, this algorithm also permits the use of the best season (represented by a set of spectral channels) for the identification and separation of cover types.

The selection of the classes that will constitute a particular node, and the set of spectral channels to be used to separate this node were based on the statistical distance between training classes. This distance was obtained by calculating the transformed divergence values of the training classes for all possible combinations of spectral channels. The best set of features to be used in each particular node was also defined using the separability information, based on a threshold of Dt=1750.

The first approach used with this classifier involved using the same 8 channel training statistics developed for the single stage Multitemporal/Multispectral classification (Figure 4). The second approach used with the layered classifier was the development of training statistics independently for each of the two dates which were then used as part of the input to the classifier (Figure 5).

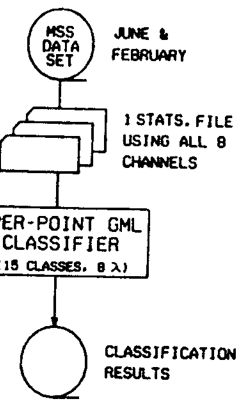


FIGURE 2. MULTITEMPORAL/MULTISPECTRAL SINGLE STAGE CLASSIFICATION, 8 CHANNELS.

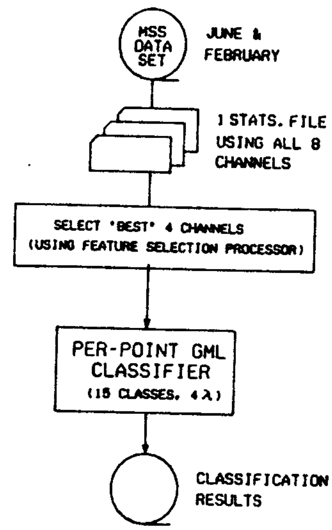


FIGURE 3. MULTITEMPORAL/MULTISPECTRAL SINGLE STAGE CLASSIFICATION, 4 CHANNELS.

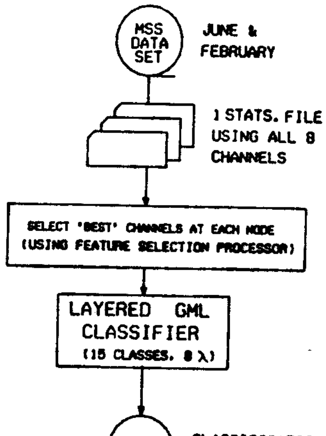


FIGURE 4. LAYERED CLASSIFIER, ONE SET OF 8 CHANNELS.

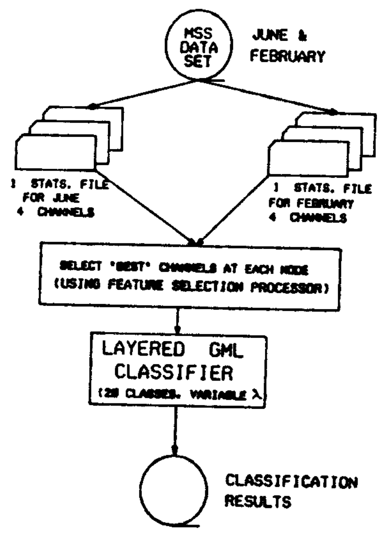


FIGURE 5. LAYERED CLASSIFIER, TWO SETS OF 4 CHANNELS.



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## Evaluation Methods

To determine the accuracy of the classification of MSS data, a set of statistically valid test fields was developed. The standard color IR composite was displayed on the Comtal Vision One/20 and a test grid with dimensions of 50 lines by 50 columns was selected as the basis for the sampling procedure, over the area where aerial photographs were available. The cell to be analyzed was selected at random. Each cell of 2,500 pixels was subdivided into four quadrants of 25 lines by 25 columns (625 pixels). One quadrant was selected at random, and the biggest, most homogeneous field corresponding to each specific cover type present in that block was identified. The minimum number of observations (pixels) used for the evaluation of any particular cover type was 100 pixels (as suggested by Landgrebe 1976).

A statistical evaluation was carried out using one-factor analysis of variance, based upon the arcsine transformation of the performance values. (This transformation was necessary because of the nature of the results -- a proportion dealing with binomial data, i.e., pixels are identified correctly or incorrectly). To determine if there were significant differences between the performance values of cover types or classifications, a Newman-Keuls Range test was performed at an alfa level of 0.1.

The criterion used for determining the cost effectiveness of the classification results was based on the amount of computer CPU time (Central Processing Unit) used to perform each classification. This was considered the most objective and accurate way to compare and evaluate the cost of each classification scheme. Because the analyst become increasingly familiar with the characteristics of the data during the sequence of analysis, it was believed that the "analyst time" required to develop the training statistics would be biased.

## RESULTS

Total CPU time required for each classification and the overall and average performances are shown in Table 4.

The Multitemporal/Multispectral single stage classifications (both eight channels and the four best channels) provided results showing detailed informational classes. For the deciduous forest, a class representing forest in shadow was identified. Bare soils were differentiated into two groups: those that are subject to flooding and those that are not. Two distinctive classes of water (deep water and shallow water) were recognized in Monroe Lake.

Figure 6 shows the classification performance by class. For the single stage classifications, both overall performance and the performances by class were very good, except for the class "Pasture" which had an accuracy of 31.5% for the 8 channel classification and 32% for the 4 channel classification. Due to confusion between the pasture and soil classes, 58% of the pasture test pixels were classified as soils in the 8 channel classification, and 50% of the pasture test pixels of the 4 channel classification were assigned to the soils classes.

Table 4. CPU time and overall classification performance.

| | CPU TIME | No. of Spectral Classes | Overall Performance | Average Performance |
|---|---|---|---|---|
| Multitemporal/ Multispectral 8 Channels | 77.3 min | 14 | 91.0% | 83.0% |
| Multitemporal/ Multispectral 4 Channels | 25.4 min | 14 | 90.8% | 83.2% |
| Layered 1 set of 8 Channels | 16.5 min | 14 | 90.8% | 82.3% |
| Layered 2 sets of 4 Channels | 9.1 min | 20 | 91.8% | 89.9% |

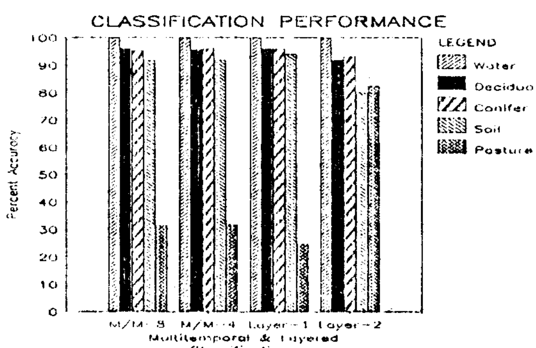


Figure 6. Classification Performance by Class.

The third classification using the layered technique (i.e., training statistics based on one set of 8 channels) showed no significant difference from the results obtained in the single stage Multitemporal/Multispectral classifications. A small decrease in the percent accuracy for the pasture class was found, but this difference was not statistically significant. The primary difficulty in classification of pasture was again due to confusion with the soil class. However, the CPU time required was only 60% (10 minutes less) of that required for the single stage Multitemporal/ Multispectral 4 channel classification.

The fourth classification (two date layered classification) had a classification accuracy of 91.8%, the best overall performance of all four classifications. Both deciduous and coniferous forest cover types had over 90% correct classification. Most of the misclassifications in each of these forest classes were actually due to confusion occurring between them rather than between forest and non-forest categories.

A more consistent classification was obtained for the non-forest classes -- over 80% as can be seen on Figure 6. The statistical comparisons of the percent correct classification for the five classes show three groups (Water, Forest and Soils-Grasslands) in which there were no significant differences in the classification accuracy. It was clear that the classification was improved due to the capabilities of the layered classifier, primarily because of this classification processor allows the analyst to select the best set of features to separate a class or group of classes.

As shown in Table 4, the overall classification performance varied only from 90.8% to 91.8%. However, in the first three classification results shown in Table 3, the average performance values indicate an important variability in relation to the overall performance values. This was caused by the very low performance of the pasture class.

Of the four classifications, the Multitemporal/Multispectral 8 channel classification required the highest amount of CPU time, followed by the Multitemporal/Multispectral 4 channel classification, then the Layered 1 set of 8 channels, and with the lowest CPU time of all four, the Layered 2 sets of 4 channels classification. Thus, based on both accuracy and CPU time, the Layered 2 sets of 4 channels approach was the best method.

## SUMMARY AND CONCLUSIONS

The results of this research show the advantage of the Layered classification approach over the Multitemporal/ Multispectral classification approach in the analysis of Multitemporal MSS data.

The single stage Multitemporal/Multispectral approach provided an adequate classification accuracy. The weak points of this scheme are: the complexity involved in the development and interpretation of the training statistics, and also the CPU time required to perform the classification. The eight channel classification required 8.5 times more CPU time than the best layered classification, and even the four channel Multitemporal/Multispectral classification required 2.8 times more CPU time than the best layered classification. The selection of the four best channels of this data set indicates that one channel of each date for each of the available regions of the electromagnetic spectrum in the MSS data are required to perform an effective multitemporal classification.

The Layered classification procedure proved to be the best in terms of classification accuracy, for both the Layered 2 sets of 4 channels and Layered 1 set of 8 channels. Although percent accuracies in the Layered 2 sets of 4 channels for the individual forest cover types were slightly lower in relation to the Multitemporal/Multispectral single stage classifications, these differences were not statistically significant. The layered technique also provided more consistent results, since all accuracies were over 80%. The design of the decision tree for the classification is one of the most important and difficult tasks in this approach.

In summary, the combination of high classification accuracy, low CPU time required and the flexibility in handling multitemporal data sets makes the Layered classifier a very effective, efficient and useful tool in multitemporal analysis of remotely sensed data.

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