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LARS Technical Report 083182

Evaluation of SLAR and Simulated Thematic Mapper Data for Forest Cover Mapping Using Computer-Aided Analysis Techniques

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EVALUATION OF SLAR AND SIMULATED THEMATIC MAPPER MSS DATA FOR FOREST COVER MAPPING USING COMPUTER-AIDED ANALYSIS TECHNIQUES

by

R. M. Hoffer, M. E. Dean, D. J. Knowlton, and R. S. Latty

Final Report

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TABLE OF CONTENTS

Executive Summary

This study involved the analysis of two very different types of data — simulated Thematic Mapper MSS data and dual-polarized X-Band Synthetic Aperture Radar (SAR) data. The first phase of the research examined the impact of the improved spatial and spectral characteristics of the Landsat-D Thematic Mapper data on computer-aided analysis for forest cover type mapping. The second part of the investigation examined, both qualitatively and quantitatively, the value of the SAR data for differentiating forest and other cover types, and assessed the utility of pattern recognition techniques for analyzing SAR data.

The study site was located in Kershaw County, South Carolina, and contained a variety of forest and other cover types, including pine, mixed hardwood, tupelo, recently clearcut areas (coming back into mixed hardwood), pasture, cropland, exposed soil, and water. Excellent quality, cloud-free TMS (Thematic Mapper Simulator) data and color infrared photography were obtained by NASA on May 2, 1979 and again on August 29, 1980 from 20,000 feet altitude, thereby providing TMS data having a nominal spatial resolution of 15 meters. The data were spatially degraded to produce data sets having 15 x 15 m, 30 x 30 m (to simulate Thematic Mapper data), 45 x 45 m, and 60 x 75 m (to simulate Landsat data) spatial resolutions.

The first phase of the analysis examined the relationships between spatial resolution and classification performance. This was followed by a sizable effort directed at examining the relationships between the numbers of wavelength bands used in classifications and the resulting classification performance, as well as the importance of different wavelength bands or portions of the spectrum on classification performance. The significance of different methods for developing training statistics and the use of different

classification algorithms were also investigated. A method for economically developing a statistically reliable test data set was also defined during this portion of the study. The final phase of the work with the TMS data involved an evaluation of Principal Components Transformations as an alternative to feature selection for reducing the dimensionality of the data.

The X-band SAR data were obtained by NASA on June 30, 1980 from an altitude of 60,000 feet. The images were digitized at J.S.C. and the two polarizations were digitally registered at LARS to produce a digital data set suitable for quantitative analysis. Initially, a detailed qualitative study evaluated the characteristics of the data and the potential for identifying various cover types on the dual-polarized (HH and HV) images. The final phase of the research involved a quantitative analysis of the SAR data which included computer classifications using both per-point (Gaussian Maximum Likelihood) and contextual (Per-Field and SECHO) classifiers.

The results of the various classifications of both the TMS and the SAR data are summarized in numerous tables and figures throughout the report. Four appendices contain 118 tables showing the classification performance results and the statistical evaluations of these results. The three major objectives of this research, as well as the several minor objectives pursued, are defined in Section II. In addition to the discussions and summarizations of the results and their significance that are contained in the body of the report, Section VI contains a complete summary of the results and some recommendations.

Results of this research that are of particular significance include the following:

1. Use of higher spatial resolution data resulted in lower overall classification accuracies when the classifications were conducted with the standard per-point Gaussian Maximum Likelihood classifier (i.e., 30 meter simulated Thematic Mapper data had lower overall classification performances than 80 meter simulated Landsat data).

2. Differences in spatial resolution caused much greater differences in classification performance among forest cover types than among agricultural cover types. (i.e., Per-point classifiers produced similar classification performances in agricultural cover types for the simulated Thematic Mapper and Landsat spatial resolution data sets, whereas for forest cover types the classification performance of the TMS data was much poorer than for the Landsat data. This was due primarily to the increased spectral variability of the forest cover types in the TMS data as compared to the Landsat data.)

3. Four wavelength bands provided the best combination of good overall classification performance and minimum computer time, although slightly higher overall classification performances were obtained by using all TMS wavebands available.

4. Overall classification performances of 85-95%, based on test data, were obtained for both the 1979 and 1980 TMS data sets when four or more wavebands were utilized in conjunction with the SECHO classifier.

5. Higher classification performances were achieved for the TMS data using a contextual classifier (SECHO) rather than Per-Point classifiers (L-2 Minimum Distance or Gaussian Maximum Likelihood).

6. Principal components transformation of the TMS data did not result in higher classification performance when using the SECHO classifier.

7. Deciduous and coniferous forest cover types can be easily differentiated on the HH polarized SAR imagery, but not on the HV imagery.

8. Pine stands and pastures cannot be effectively differentiated on either the HH or HV SAR imagery, in spite of the distinct differences in physical characteristics of these two cover types.

9. Significant improvements in overall classification performance of the SAR data were achieved using contextual classifiers (Per-Field and SECHO) as compared to the GML per-point classifier.

10. Since only one wavelength (X-Band), represented by two channels (HH and HV polarizations) of SAR data were available for analysis, overall classification performances of only about 65% were obtained with the SAR data. It is believed that additional wavelengths of SAR data would enable significantly higher classification performances to be achieved.

11. SAR data to be used for computer analysis in future projects (e.g., multi-frequency, multi-polarization) should be obtained through an all-digital processing system in order to minimize between-channel spatial distortions in the final data set.

List of Tables

List of Figures

Acknowledgements

Many people have been involved in various aspects of this research, and their efforts are gratefully acknowledged. Particular recognition and a heart-felt "thank you" is hereby given to my fellow authors of this Final Report — Mr. Douglas Knowlton, Miss Ellen Dean, and Mr. Rick Latty — who as graduate students in the Department of Forestry and Natural Resources, Purdue University, spent many, many long hours processing and analyzing the TMS and SAR data used in this work. Special acknowledgement is also given to the efforts of Mr. Norman Hatcher, the NASA Technical Monitor, for help in obtaining the data and for many helpful suggestions and questions throughout the project; Mr. Dennis Taylor of Lockheed Corporation at NASA/JSC for help in digitizing the SAR imagery; Mrs. Kathy Kowlowski, LARS, for preprocessing and registering the digitized SAR data; Mr. Bud Goodrick, formerly of LARS, Dr. Luis Bartolucci and Mr. Paul Anuta of LARS, for assistance in various aspects of the data processing and analysis; Mrs. Brenda Prather for secretarial support throughout most of the project; and Miss Patty Karnehm for typing and preparing all of the tables as well as the text of this final report. Acknowledgement is also made of the efforts of the NASA/JSC personnel who were involved in obtaining and processing the TMS and SAR data as well as the color infrared photography used in this project. Finally, appreciation is expressed to NASA/JSC for the financial support of this research.

Roger M. Hoffer
Principal Investigator

I. INTRODUCTION

Tremendous progress has been made over the past few years in demonstrating the potentials and limitations for utilizing Landsat MSS data and computer-aided analysis techniques for identifying and mapping various earth surface features, including major forest cover groups (deciduous and coniferous) and, in some cases, individual forest cover types. The Thematic Mapper scanner system, launched on Landsat-D in July 1982, has increased spectral and spatial resolution, as well as an increase in the number of channels, which should theoretically allow better and more accurate classification of ground features. Past experience with aircraft, Landsat, and Skylab MSS data indicates that the spectral characteristics (both location and width) of the wavelength bands on the Landsat-D Thematic Mapper system should allow more accurate identification of forest cover types to be achieved using computer-aided analysis techniques (Coggeshall and Hoffer, 1973; Hoffer and Staff, 1975; Hoffer et al., 1975). The impact of the improved spatial resolution is not obvious, due to the interaction between the textural characteristics of some types of forest cover (e.g., large-crowned mature deciduous trees) and the spectral response of individual high resolution pixels (Kan and Ball, 1974; Sadowski and Sarno, 1976). This investigation was therefore directed at examining the impact of the improved spectral and spatial characteristics of the Landsat-D Thematic Mapper data on computer-aided analysis for forest cover type mapping.

A second major phase of this investigation involved X-band Synthetic Aperture Radar (SAR) data. Radar systems have several unique advantages over optical systems. Such advantages include the capability to penetrate clouds, to be operated day or night, and to obtain imagery in which the tone and texture characteristics are related to the dielectric constant and physiognomic properties of the cover types present. The side-look angle of radar systems also produces characteristics in the data that are not found in data from multispectral scanner systems. Because of the different and perhaps unique characteristics of radar data, the question was raised as to whether X-band radar systems could provide more effective data for differentiating forest cover types and density differences than can be obtained using MSS data from the optical portion of the spectrum. Earlier work in the mid-1960's with K-band imagery showed that some vegetative cover types could be differentiated and that differences were sometimes apparent in dual-polarized data (Morain and Simonett, 1966, 1967). However, these early studies did not involve X-band data and did not indicate which polarization provided the best capability for discriminating among forest cover types. Further, none of the earlier work had involved the utilization of computer-aided analysis techniques. Therefore, in addition to the question concerning the value of radar data for differentiating forest cover types and density differences, this investigation also was directed at evaluating the potential for using "standard" computer classification techniques, previously developed for multispectral scanner data, for analyzing dual-polarized X-band radar data.

II. OBJECTIVES

This research involved three primary objectives:

1. To determine the impact of the spatial resolution characteristics of the Thematic Mapper MSS data on classification of forest cover types using computer-aided analysis techniques.
2. To determine the impact of the improved spectral characteristics of the Thematic Mapper MSS data, as compared to Landsat I-III data, on the capability to accurately and efficiently classify forest cover types using computer-aided analysis techniques.
3. To evaluate the utility of dual-polarized, X-band synthetic aperture radar data for identifying and mapping various forest cover types, and for determining differences in density and condition of the forest cover.

Each of these major objectives included several sub-objectives which can be defined as follows:

1a. To compare classification performance of 30 meter (simulated Thematic Mapper) data to 80 meter (simulated Landsat) data, using a per-point classifier.

1b. To compare classification performances, based on a per-point classifier, using data of four different spatial resolutions (15 m, 30 m, 45 m, and 80 m).

1c. To evaluate the impact of spatial resolution on spectral variability of different cover types, with special emphasis on both forest and agricultural cover types.

1d. To evaluate the effectiveness of a contextual classifier (i.e., SECHO), as compared to per-point classifiers (L-2 Minimum Distance and Gaussian Maximum Likelihood), for classifying data of relatively high spatial resolution such as the 30 m data to be obtained by the Thematic Mapper.

2a. To define the minimum number of wavelength bands needed to achieve an acceptable classification result.

2b. To evaluate the importance of the different portions of the spectrum for accurately classifying the various forest, agricultural, and other cover types.

2c. To determine whether different sub-sets of wavelength bands are needed to classify different cover types, or if a single combination of wavelength bands is adequate for all cover types.

2d. To evaluate the impact of different methods of developing training statistics on the classification results (both overall and for individual cover types).

2e. To determine the impact of principal components transformations on overall and individual cover type classification performances.

2f. To determine the minimum number of principal component channels required to achieve satisfactory classification results.

2g. To evaluate the impact of different classification algorithms, using 30 meter simulated Thematic Mapper data, for both transformed and untransformed data sets.

3a. To qualitatively evaluate the potential for differentiating forest and other cover types using dual-polarized X-band SAR data.

3b. To evaluate, qualitatively and quantitatively, the relationship between radar look angle and magnitude of the radar return.

3c. To quantitatively determine the potential for classifying forest and other cover types using dual-polarized X-band SAR data and a Gaussian Maximum Likelihood classification algorithm.

3d. To evaluate the impact of degrading the spatial resolution of SAR data on classification accuracy.

3e. To determine the effectiveness of contextual classifiers (i.e., Per-Field and SECHO), as compared to a per-point classifier (Gaussian Maximum Likelihood) for classifying SAR data.

3f. To compare the effectiveness of dual-polarized X-band SAR data to that of TMS data for purposes of classifying forest and other cover types.

III. STUDY SITE DESCRIPTION

The study site is located in Kershaw County in central South Carolina, situated on the escarpment between the Piedmont platteau and the coastal plain. The geographical location of the study site and the orientation of the flight lines used are shown in Figure 3.1. The area changes from a distinctly dissected region having moderate topographic variability in the north to a river bottom area of gently sloping terrain in the south along the Wateree River. The soils of the northern area are acid clays of low permeability. These grade into loamy sediments in the river bottom area to the south. The more upland soils of the south are characterized by higher sand fractions. The geomorphological diversity of the area results in a wide variety of vegetation cover classes, and there is also a considerable variability in spectral characteristics associated with each cover class. These complexities make the area a prime choice for testing various remote sensing techniques. The area was selected by the U.S. Forest Service as one of two primary sites in the U.S. to be used in testing various remote sensing techniques having potential use in forest inventory operations.

The southeastern portion of the study area has flat to very gently rolling topography which provides a minimum of environmental variability, with the result that single cover classes occupy large contiguous areas. The exception is water tupelo which requires a narrow range of water fluctuation levels and therefore occupies rather restricted areas. The major cover classes of the southern area are bare soil, pasture, crops, pine, pine-hardwood mix, hardwood (both old age and second growth), water tupelo, clearcut areas, marsh vegetation and water. The bare soil areas are generally associated with agricultural activities or are areas of recent clearcuts. Areas in crops are

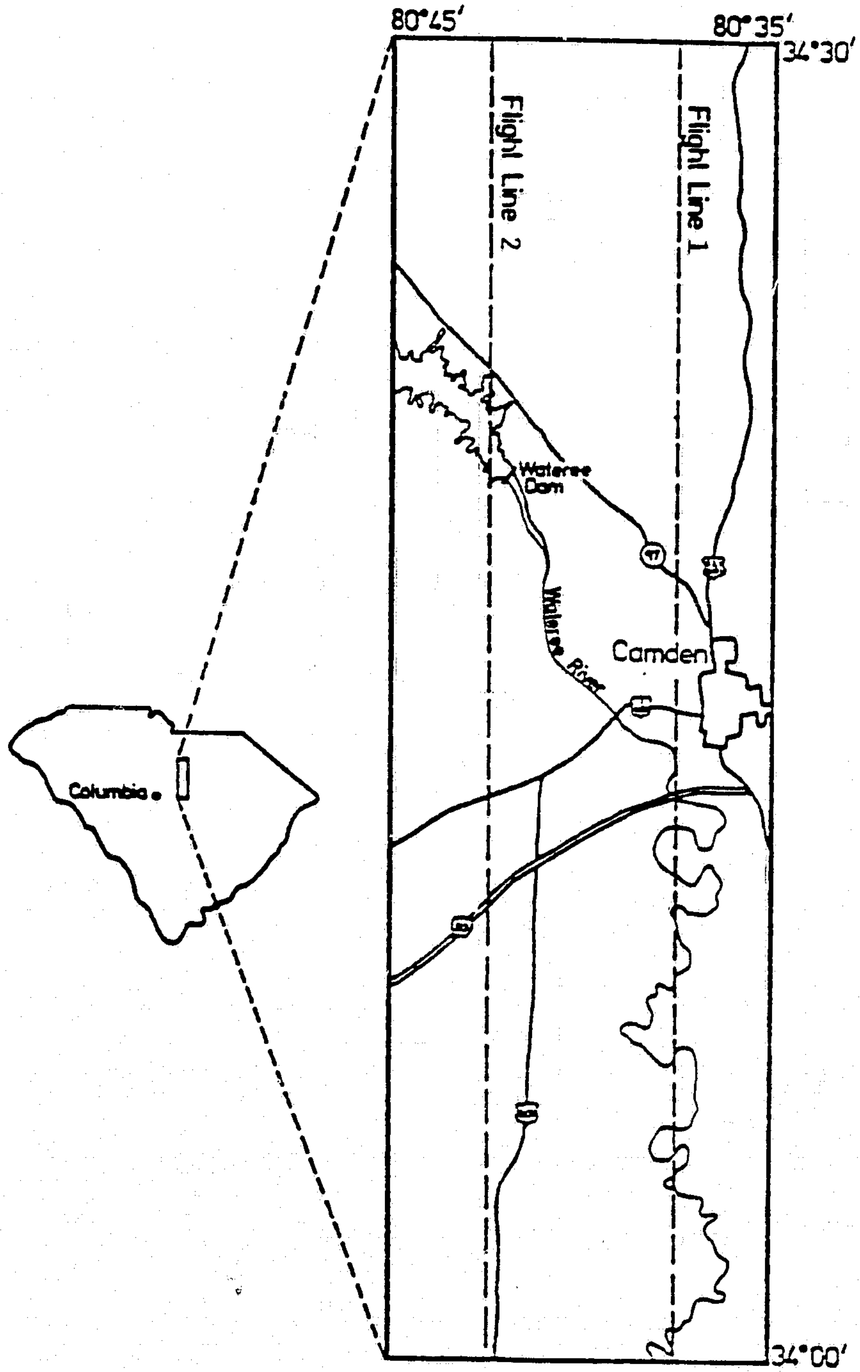

Figure 3.1. Location and schematic representation of the South Carolina study area.

associated with a wide variety of ground cover conditions, ranging from primarily bare soil to closed crop canopies, depending on the amount of time since planting. Similarly, the clearcut areas vary in ground cover condition depending on the length of the period since cutting. Areas of saturated soil and standing water in some of the clearcuts increase the diversity of spectral characteristics associated with that information class. A considerable diversity in age classes exists for the pine stands and also for the pine-hardwood mix, with consequent variations in canopy closures. The pine stands are generally planted slash or loblolly pine. The hardwood (other than the stands of tupelo) consist of mixtures of several species including sweetgum, black willow, and sycamore. The water class is primarily contained in the Wateree River, although there are also some spectrally distinct ponds associated with a gravel mining operation in the southern portion of the test site.

The northern area, being heavily dissected and having somewhat steeper terrain, contains cover classes which generally do not occupy large contiguous areas. The major cover classes are bare soil, crops, pasture, pine, pine-hardwood mix, hardwood, clearcut, water, and urban. The pine areas vary in crown closure more in the north than in the southeastern region. The hardwoods are generally restricted to relatively narrow gully bottoms. Areas in crop and pasture are generally very small due to the size of areas suitable for agricultural practices. Most of the surface area in water is in the Wateree Reservoir, therefore providing a ratio of the frequencies of boundary-to-nonboundary pixels very different from that in the south.

IV. THEMATIC MAPPER SIMULATOR (TMS) DATA ANALYSIS

A. Data Collection

1. TMS Data

The 1979 MSS data used in this study were collected by the NASA NS-001 Thematic Mapper Simulator (TMS) on May 2, 1979 as part of NASA Flight Mission 399. Table 4.1 shows the wavelength bands of the TMS scanner and the corresponding Landsat-D Thematic Mapper bands. The TMS data were obtained in mid-morning under cloud-free conditions from an average height above ground of 19,500 feet (5,944 meters). At this altitude, the 2.5 milliradian IFOV of the NS-001 scanner provided a 15.3 meter ground resolution element at nadir. Unfortunately, the 2.08-2.35 μm band (Channel 7) was inoperable at the time of the flight mission, but all other instrumentation was functioning normally. Color and color infrared photographs of excellent quality were taken at the same time the scanner data were obtained. The photographs and documented observations of ground conditions from visits to the study area provided the reference data for the study, as discussed later.

In 1980, NASA attempted to obtain a near-simultaneous set of TMS and Synthetic Aperture Radar (SAR) data to be used in the analysis of a combined data set and also to provide a second set of TMS data for evaluating the repeatability and reliability of the results obtained with the 1979 data. NASA Flight Mission No. 425 was flown on July 2 and 3 by the NC-130 aircraft to obtain NS-001 TMS data. However, significant levels of cloud cover in key portions of the flight lines caused the TMS data obtained to be of marginal value. Consequently, on August 29, 1980 NASA Flight Mission No. 430 was flown, and resulted in a usable set of TMS scanner data, and color and color infrared photography. The data were obtained between 10:00 and 11:00 A.M. from an

Table 4.1. Channel configuration of the NS-001 and Landsat-D Thematic Mapper Scanner systems.

NS-001		Thematic Mapper	
Channel Number	Band	Channel Number	Band
1	0.45 - 0.52	1	0.45 - 0.52
2	0.52 - 0.60	2	0.52 - 0.60
3	0.63 - 0.69	3	0.63 - 0.69
4	0.76 - 0.90	4	0.76 - 0.90
5	1.00 - 1.30	no corresponding channel	
6	1.55 - 1.75	5	1.55 - 1.75
*7	2.08 - 2.35	6	2.08 - 2.35
8	10.4 - 12.50	7	10.4 - 12.5

*Channel 7 of the NS-001 scanner was inoperable during data collection mission of May 2, 1979.

altitude of 21,000 feet (MSL) over the Camden test site. The data obtained from this mission was essentially cloud free in the southern portion of Flight Line 1 (south of Camden) but there were varying degrees of cloud cover in the northern portion of Flight Line 1 and over Flight Line 2. As a result, analysis of the 1980 TMS data was concentrated on the area in Flight Line 1 south of Camden. All 8 channels of the NS-001 scanner functioned properly during the August 29 mission. Flight lines were flown from north to south, which simplified some of the subsequent data handling activities.

2. Reference Data

On-site examinations of the study area were conducted three times throughout the study. The first set of reference data were obtained from May 10-15, 1979 in support of the TMS data obtained on May 2, 1979. ASCS photography was obtained and used for this initial site visit. The characteristics of the cover type were documented at 84 locations throughout the test site and these locations were noted on the ASCS photos and USGS maps. Detailed information concerning ground conditions at the various locations visited throughout the study site are contained in the first quarterly progress report (June 1, 1979 - August 31, 1979), LARS Contract Report 083179.

In addition to the 1:40,000 scale color and color infrared photography obtained by NASA at the time of the NC-130 flight missions, larger scale photography (1:12,000 and some 70 mm 1:6,000 and 1:2,000 color transparencies) were obtained from the USDA Rocky Mountain Forest and Range Experiment Station, courtesy of Mr. Robert Aldrich. These U.S. Forest Service photos were obtained in 1977 over selected portions of the study site and offered some information concerning the characteristics of the forest cover in the study area.

A second site visit was conducted from July 1-3, 1980, in conjunction with the radar mission on June 30 and the unsuccessful TMS data collection effort of July 2 and 3. The third visit to the test site was conducted from July 19-22, 1981, for the purpose of evaluating results of the TMS classifications and the radar imagery analysis. For this last site visit, a number of areas had been defined during the course of the analysis, and these were examined on the ground to verify the cover type characteristics. Both the second and third field trips included observation flights in a Cessna over the study area. These "birds-eye" views of the study area were particularly useful, in that some parts of the site were nearly inaccessible on the ground, and the aerial vantage provided an effective method for quickly comparing several test site locations in the data. These site visits also provided an opportunity for all personnel working with the data to become reasonably familiar with the test site and the characteristics of the cover types in the study area. Such site visits are absolutely necessary in this type of project and of tremendous benefit to the research personnel involved.

B. Data Handling

1. Reformatting

The 1979 TMS data had been flown from south to north so part of the reformatting process involved reversing both flight lines and individual scan lines so that they could be displayed with north at the top of the image and without a mirror image effect in the individual scan lines. Appropriate ancillary data was also inserted into the header information for the data tapes at the time of the reformatting.

2. Geometric Adjustment

The variation in viewing angle (i.e., $\pm 50^{\circ}$ from nadir) inherent in aircraft scanner data, results in geometric distortions in the data which hamper determination of in-place location and area estimates. The objectives of the geometric adjustment were to 1) produce a data set which corresponded geometrically to the USGS maps of the area and the aerial photography, in order to facilitate the location and identification of training and test fields and 2) to provide a data set which would allow accurate area estimates to be obtained from pixel summaries.

The criteria used in evaluating the quality of the geometric adjustment procedures were 1) whether the scale was consistent in each dimension everywhere in the data set and 2) equivalency of scale between the two dimensions (i.e., whether a fixed distance on the ground could be accurately determined by a defined number of columns or lines of scanner data).

Note that the scale could be consistent in each dimension, but could still be very much in error in terms of actual ground dimensions involved. For instance, the original scanner data had a considerable distortion in equivalency of scale due to over-scanning. As a result, when each scan line was displayed individually, dimensions along the flight line at nadir were approximately twice what they were across the flight line.

The instantaneous field of view (IFOV) of the scanner, the average height above ground of the aircraft, and the change in scan angle corresponding to the analog signal sampling interval were employed to model the geometry that resulted from the variable viewing angle of the scanner optics. This provided a means for adjusting the across track distortions in the original scanner data. A program was written to adjust for the geometric distortions along each scan line, and 14 pairs of control points were established at random in the data set to evaluate the effectiveness of the geometric adjustment program. Both the consistency of scale in each dimension and the equivalency of scale between dimensions (i.e., along track and across track) were evaluated by superimposing the control points (which were located on a 1:62,500 USGS map) onto the geometrically adjusted imagery using a Bausch and Lomb Zoom Transfer Scope. The coincidence of all control points between the map and the scanner data indicated that the geometric adjustment had been successful. The details of the geometric adjustment procedure are given in the second quarterly progress report (September 1, 1979 - November 30, 1979), LARS Contract Report 120379, and in Latty (1981).

3. Radiometric Adjustment

Changes in viewing angle of the scanner relative to the angle of incident radiant energy can provide a major source of variance in the spectral response values recorded. Examination of the 1979 scanner data indicated that there appeared to be distinct changes in response levels along individual scan lines, even though cover types did not change. These changes in reflectance associated with changes in viewing angle were confirmed by plotting average reflectance values by column over data blocks containing the same cover type, on a channel by channel basis. These plots showed that even though the cover type was the same and there were no significant topographic effects in this portion of the study area, the average reflectance values were considerably different as a function of column in the data set (see Figure 4.1). These differences were therefore ascribed to scanner look angle/illumination angle effects. Software was then developed to radiometrically adjust the data in order to remove or reduce the variance in reflectance caused by changes in viewing angle which were extraneous to differences in cover types.

For the 1979 data, four areas in the data set which appeared to have no across tracks stratification of cover type were identified, and a program was developed which computed the average reflectance by column for each channel over all of the scan lines in the designated areas. A regression analysis was then run for each channel using first, second and third degree polynomials. Evaluation of these results indicated that a third degree polynomial would provide an adequate fit to the data. Predicted reflectance values were then computed for each column, and for each channel. The predicted reflectance at nadir was divided by the predicted reflectance of each column, for each channel, and the actual MSS response values were multiplied by this quotient and these radiometrically adjusted data values were written onto another tape. The second quarterly progress report contains a more detailed discussion of the radiometric adjustment procedure, as well as a discussion concerning the theoretical considerations involved in such radiometric adjustment procedures.

The method used to adjust the 1980 data set was somewhat different than that used for the 1979 data. In 1979, homogeneous blocks covering the full width of the scanner data which appeared to have no across-track stratification of cover type were identified. However, data blocks which fully met this

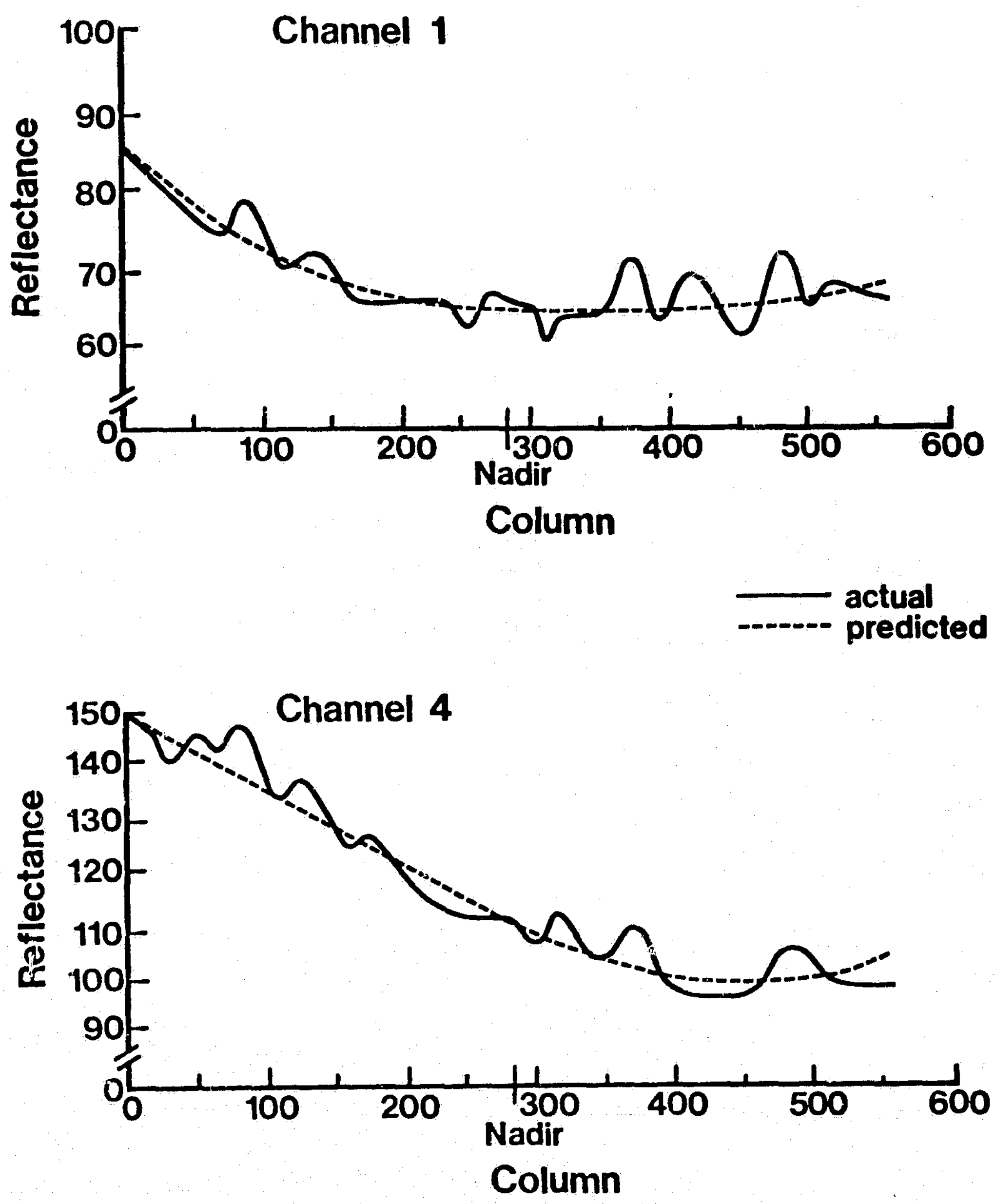

Figure 4.1. Actual and predicted radiometric response level values, as a function of column, for Channels 1 and 4, 1979 TMS data.

criterion could not be defined in the 1980 data set. Therefore a method was devised which consisted of looking at homogeneous blocks of a single cover type which were located at regular intervals across the flight line. A set of columns, each of which was 20 pixels wide, was marked across the flight line and homogeneous blocks of old growth hardwood were located within each column group (see Figure 4.2). Figure 4.3 shows the coincident spectral plots of the old growth hardwood in the different column groups for each wavelength band, prior to radiometric adjustment. This figure clearly shows that the variation in spectral response as a function of look angle is much more important in the near infrared than the visible portion of the spectrum, and of relatively little importance in the middle or thermal infrared wavelengths. It also shows some irregular shifts in radiometric response in certain columns, probably caused by differences in the characteristics of the stands involved.

The regression analysis was conducted using the same software that had been developed for the 1979 data set, and the data were adjusted using the empirically derived quotients. In evaluating the effectiveness of this radiometric adjustment procedure on the 1980 data, it was determined from the regression analysis that as one moved across the flight line, the X-variable (location across flight line) was not significant at an alpha level of 0.05. This result indicated that the radiometric adjustment had been successful in removing the effect of changes in view angle. Figure 4.4 shows an example of the unadjusted 1980 MSS data and Figure 4.5 shows the same area after it had been radiometrically adjusted. Details of the analysis of the 1980 radiometric adjustment procedure were contained in the eighth Quarterly Progress Report (March 1, 1981 - May 31, 1981), LARS Contract Report 053181.

4. Spatial Resolution Degradation

Due to the 2.5 milliradian IFOV of the NS-001 multispectral scanner and the average flying height of approximately 20,000 feet (or 6,560 meters) above

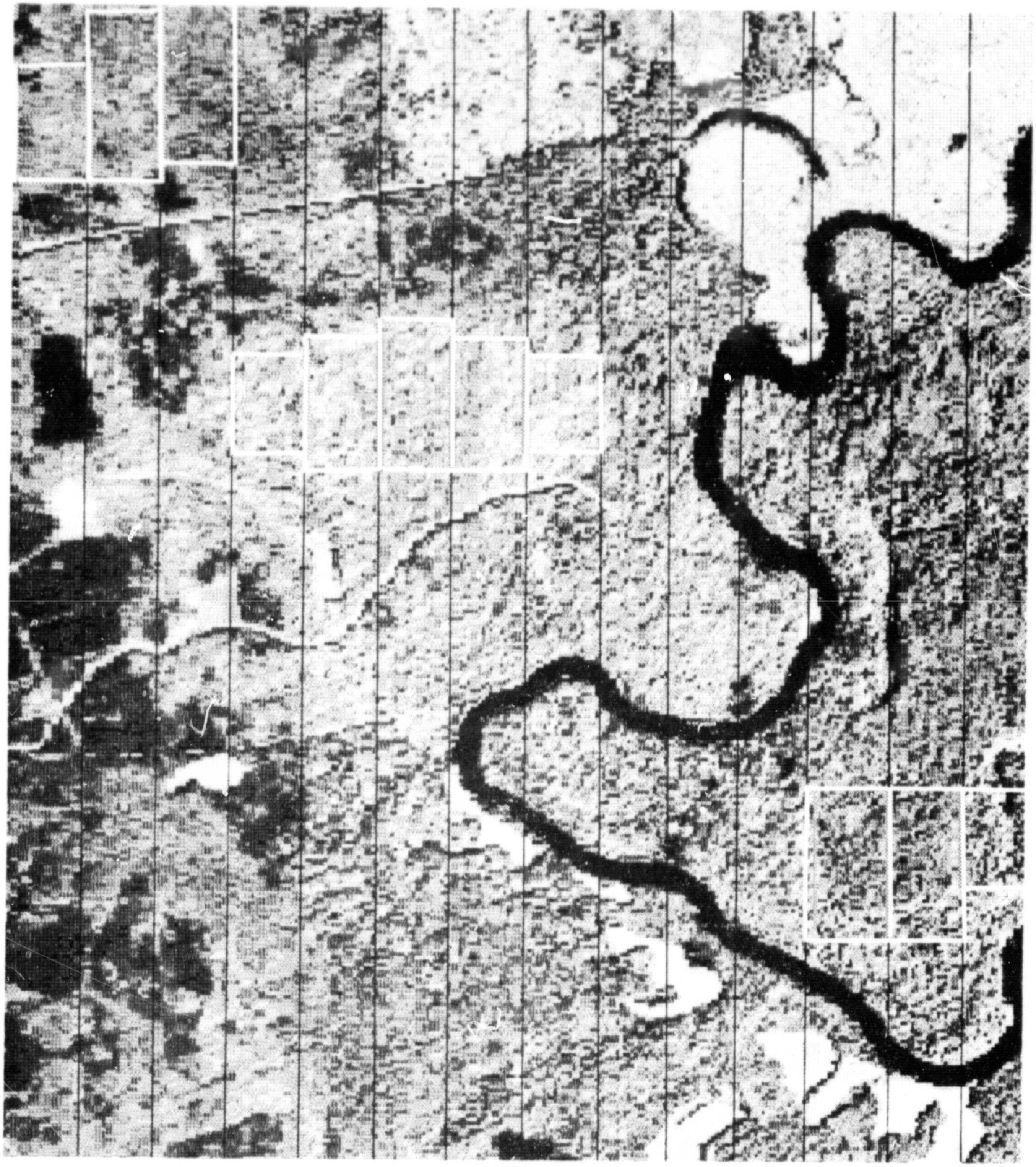

Figure 4.2. Location of fields within the column groups for a portion of the flight line.

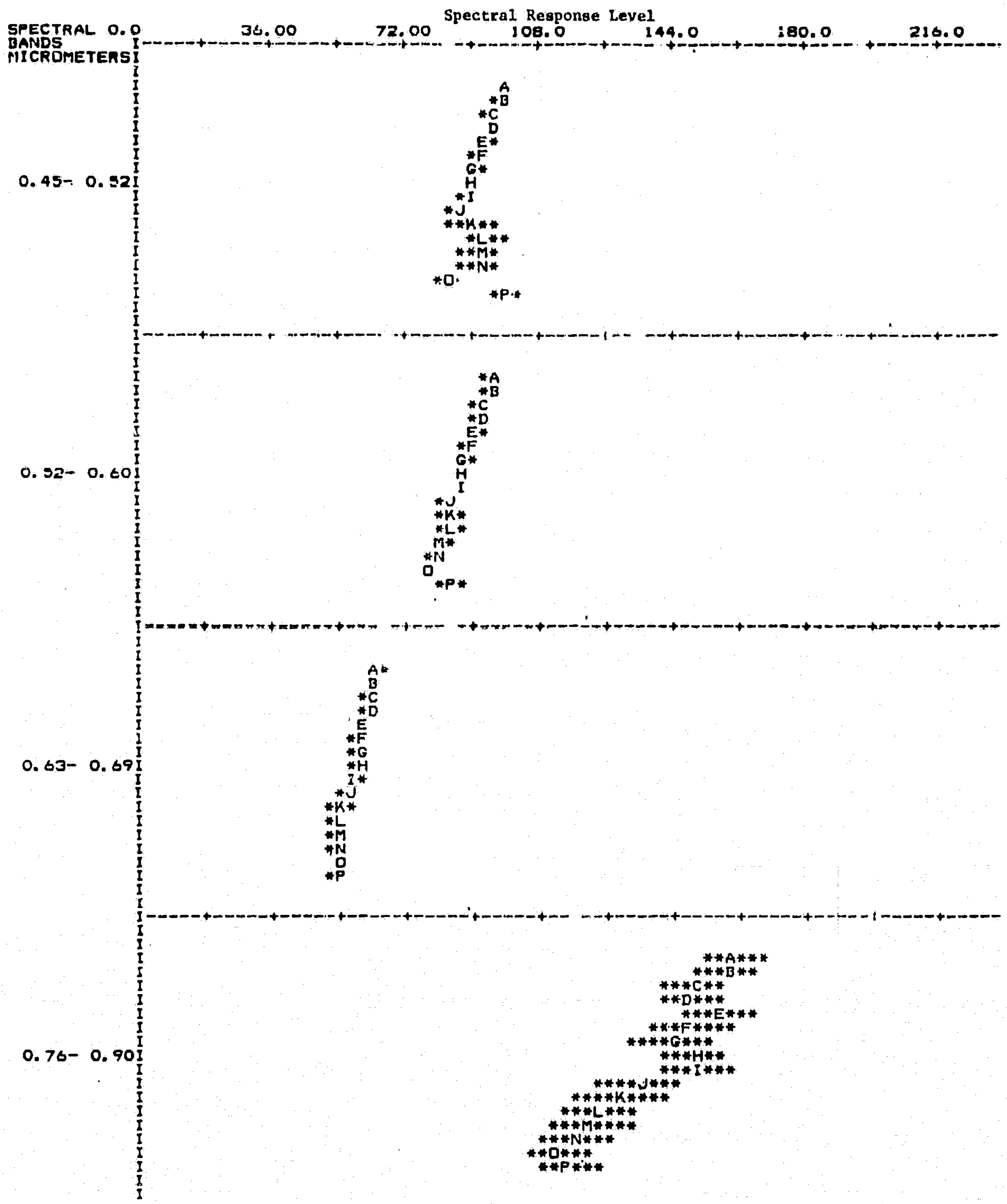

Figure 4.3. Coincidental spectral plots of the old growth hardwood in different column groups prior to radiometric adjustment.

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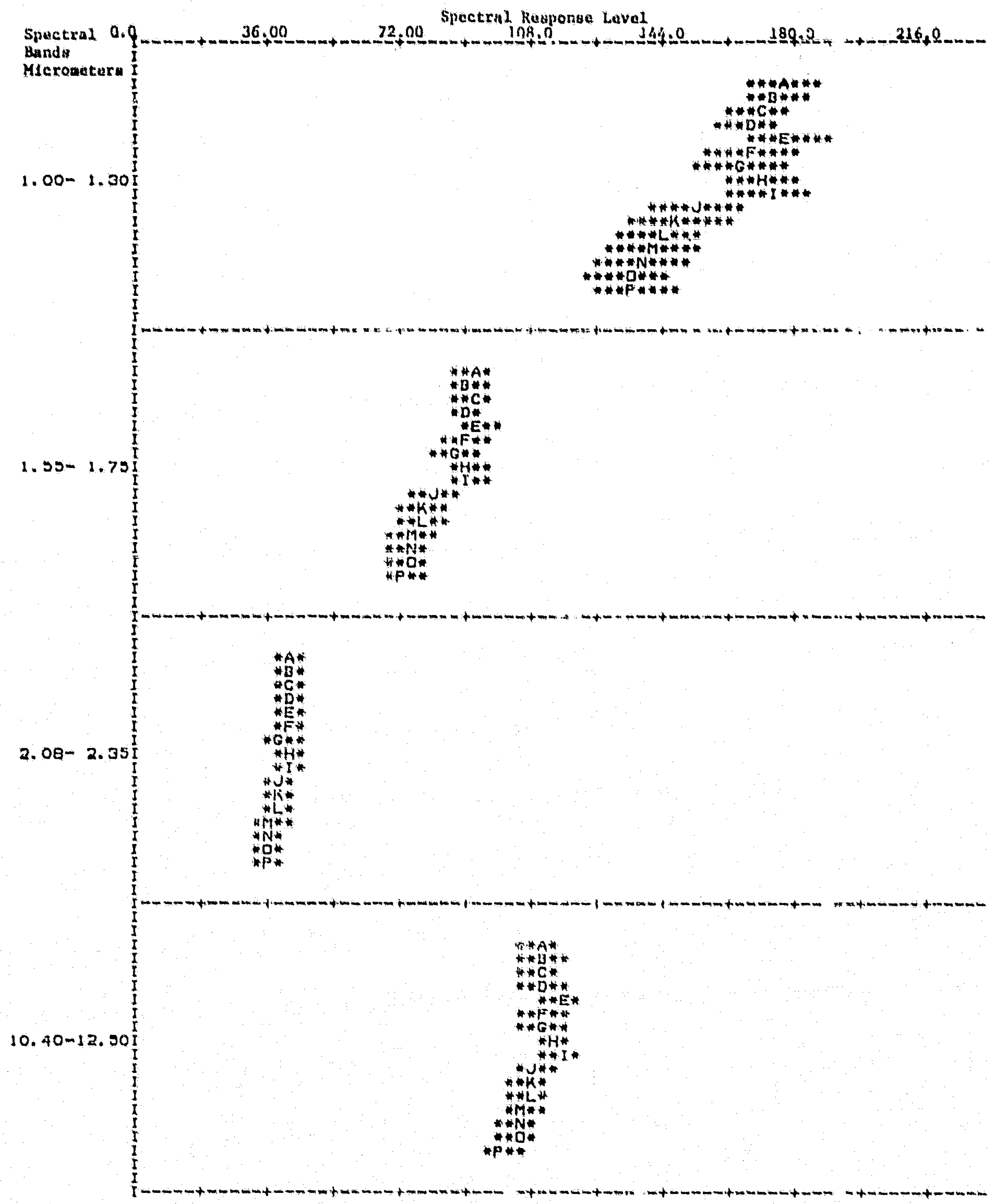

Figure 4.3, Continued.

Figure 4.4. Varian imagery of the radiometrically unadjusted 1980 MSS data (channel 5).

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Figure 4.5. Varian imagery of the radiometrically adjusted 1980 MSS data (channel 5).

ground, the original data had a nominal spatial resolution at nadir of approximately 15 meters. Neighboring pixels of the 1979 data were averaged together to provide data sets of approximately 30 x 30 meters (corresponding to the proposed Thematic Mapper), 45 x 45 meters, and 60 x 75 meters (corresponding to the current Landsat data). (The 60 by 75 meter data set is subsequently referred to as "80 meter" data, implying a resolution approximating that of the Landsat MSS.) The averaging was unweighted due to an insufficient number of pixels to provide a continuous function required to simulate the point spread function of each of the respective spatial resolutions. A separate tape file was constructed for each resolution from each flight line segment. Figures 4.6a, b, c, and d are illustrations of small portions of the greyscale imagery in Channel 5 for each spatial resolution. These figures are rather dramatic examples of the significance of spatial resolution on the characteristics of the data used to study and map earth surface features.

Figure 4.6. Examples of TMS data in channel 5 at each of the spatial resolutions studied. a. 15 x 15 meter.

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Figure 4.6 (continued) b. 30 x 30 meter.

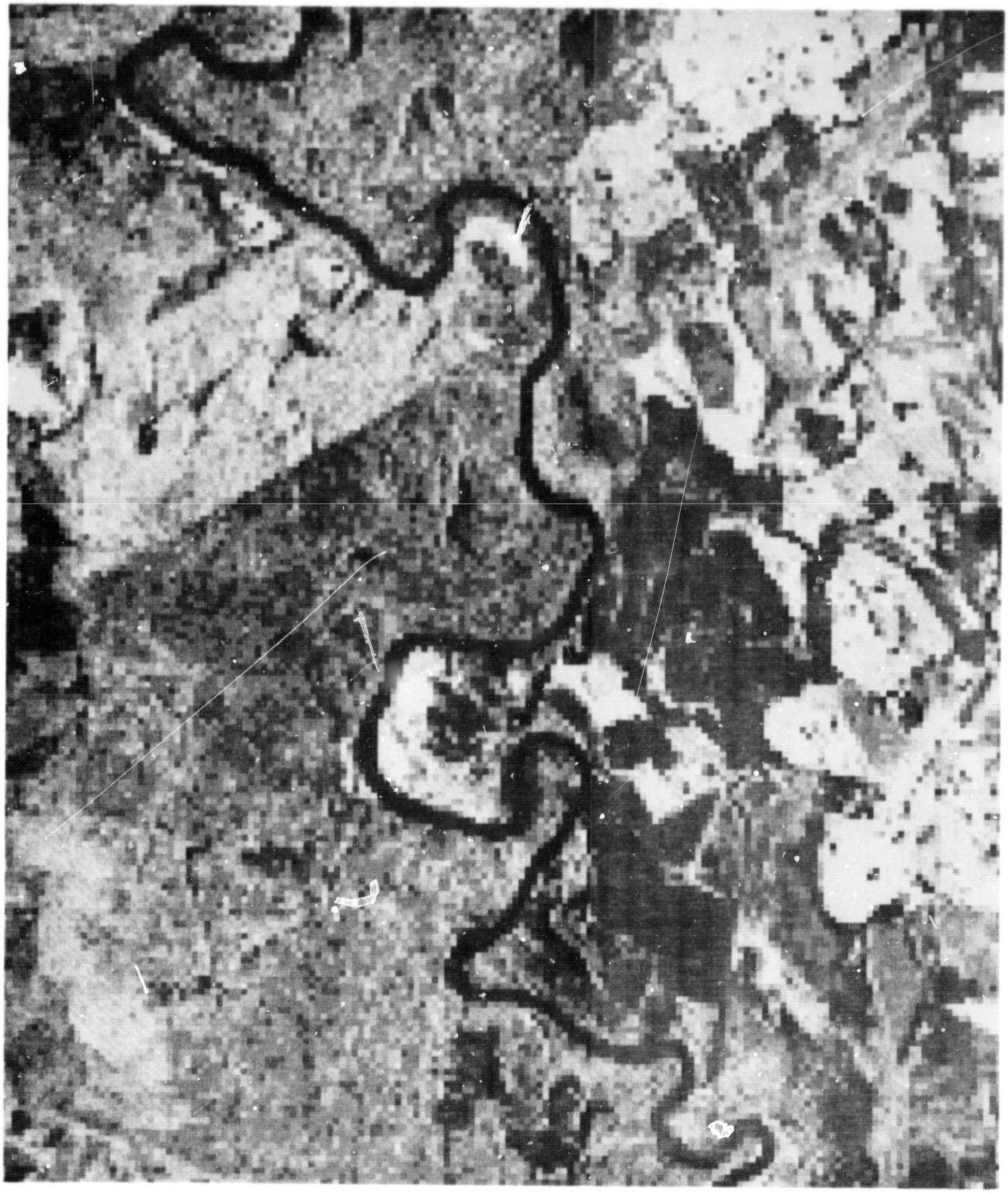

Figure 4.6 (continued) c. 45 x 45 meter.

Figure 4.6 (continued) d. 60 x 75 meter.

C. Evaluation of Spatial Resolution on Classification Performance

1. Development of Training Statistics

This phase of the research was conducted using the 1979 data. Training statistics were developed using a supervised clustering approach. Two 512 x 512 blocks of the 15 meter spatial resolution data were displayed on the COMTAL Vision One/20, using data from channels 3, 4, and 5 (0.63-0.69 μm, 0.73-0.90 μm, and 1.00-1.30 μm, respectively). Areas representing each of the eleven cover classes referred to in the test site description were identified using the digital imagery and the 1:40,000 color infrared aerial photographs, and the line-column coordinates were recorded. FORTRAN programs were written to convert the line-column coordinates of the 15-meter spatial resolution COMTAL image into the 15, 30, 45, and 80 meter spatial resolution coordinates of the MIST (Multispectral Image Storage Tape). A total of 224 training fields were defined for the analysis. Table 4.2 shows the number of training fields identified in each cover class and the average number of pixels per training field for each of the spatial resolutions.

The reduction in sample sizes for the coarser resolutions was regarded as a natural consequence associated with coarser resolution data and, therefore, no effort was made to compensate this effect by providing a proportionately greater number of training fields for the coarser resolutions. The relatively low number of pixels employed with the coarser spatial resolution data for developing training statistics using the supervised training field technique may have resulted in lower classification accuracies than would have been achieved using other training techniques that had previously been shown to be well suited for Landsat resolution data.[1/] However, using different techniques

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[1/] Fleming (1977) examined several training techniques and found an unsupervised clustering approach ("multicluster blocks") particularly well

Table 4.2. The Number of Training Fields Defined for each Cover Class and the Average Number of Pixels per Training Field for Each Spatial Resolution (1979 TMS Data).

Cover Class	No. of Training Fields	Spatial Resolution 15 Meter	30 Meter	45 Meter	80 Meter
Soil	35	223.0	55.6	25	11.0
Past	51	75.7	19.4	8.0	3.8
Crop	34	168.6	42.5	18.4	8.9
Pine	16	204.4	50.3	23.1	9.8
Pihd	4	318.2	78.5	35.7	15.2
Hdwd	17	926.2	235.1	104.8	46.6
Sghd	16	557.7	140.1	60.9	28.8
Tupe	17	82.0	20.6	9.1	4.1
Ccut	22	772	194.4	85.9	40.7
Mveg	2	596	147.0	65.0	28.0
Watr	10	182.7	42.8	20.3	11.1
Total	224	303.6	76.3	33.7	15.5

to develop the training statistics would have added another variable to the classification accuracy comparisons, which was not desirable.

The fields were grouped by cover class and each cover class group was clustered separately for each resolution.[2/] The cluster analysis resulted in a total of thirty-three spectral classes representing the eleven cover classes. Table 4.3 shows the spectral classes defined and the number of pixels clustered into each spectral class, for the data of each spatial resolution. Pooling and deleting of cluster classes was avoided where possible to avoid introducing different analyst effects in the spectral classes associated with the data of each spatial resolution. One spectral class of water for the 45 meter data had to be deleted from the training statistics due to an insufficient number of pixels to compute the covariances. The pair-wise separabilities of the spectral classes were examined across cover class, within each resolution. Based on the class separabilities, the spectral classes were considered appropriate for classification purposes.

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suited for developing training statistics in using Landsat data. In this approach the analyst locates several blocks in the data. Each block contains a multiple of cover classes and cover class conditions. The blocks are selected with the intention of representing all of the cover classes, and the variation of their conditions, contained in the area to be classified. The blocks are then clustered independently, or in groups, depending on the size of the blocks and the dimension restrictions associated with the clustering program. The analyst then identifies the cover class corresponding to each cluster class. Employing such a "multicluster blocks" technique with high resolution aircraft data was expected to result in pixels from different cover classes being clustered into common cluster classes due to spectral similarities among areas within the different cover classes. A pilot clustering of blocks of data containing several cover classes confirmed this expectation.

[2/]The convergence parameter was set to 98.5 percent, which means the percent of pixels which are not reassigned in the last iteration of pixel assignment to the nearest (Euclidean distance) mean is not less than 98.5 (Phillips, 1973).

Table 4.3. The Number of Pixels in each Spectral Class of each Cover Class, by Spatial Resolution.

Cluster Class	Spatial Resolution 15 Meter	30 Meter	45 Meter	80 Meter
Tupe 1	511	139	72	27
Tupe 2	452	104	36	20
Tupe 3	403	99	45	21
Mveg 1	658	158	68	29
Mveg 2	534	136	62	27
Crop 1	598	130	58	28
Crop 2	2887	746	312	152
Crop 3	1003	266	127	65
Crop 4	1227	299	126	54
Past 1	432	112	37	18
Past 2	572	164	70	61
Past 3	1154	296	127	21
Past 4	1233	303	137	68
Past 5	419	104	36	23
Soil 1	765	375	184	83
Soil 2	1919	909	428	187
Soil 3	1366	662	259	114
Pihd 1	246	72	28	16
Pihd 2	1015	242	115	45
Hdwd 1	1159	1319	693	335
Hdwd 2	1846	1701	656	268
Hdwd 3	1043	955	418	189
Ccut 1	771	714	335	157
Ccut 2	1480	1294	582	285
Ccut 3	1414	1445	634	280
Ccut 4	666	732	324	132
Sghd 1	1597	909	428	203
Sghd 2	1979	817	324	139
Sghd 3	757	396	187	93
Pine 1	1244	356	156	85
Pine 2	1946	429	205	72
Watr 1	925	215	*	11
Watr 2	164	39	121	53

*Spectral class was deleted due to an insufficient number of observations to compute the covariance.

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2. Development of Test Data Set (1979 TMS Data; Spatial Resolution Study)

A set of test areas were defined independent of the areas used for training the classifier. Such a test data set provides an estimate of the classification accuracies expected to be achieved with data of each spatial resolution examined. Since the accuracy estimates were obtained in areas selected independently from the training areas, the classification accuracy estimates would apply to all pixels of the area classified which satisfy the test pixel selection criteria. A method was developed which provided the test pixels for all four spatial resolutions simultaneously, and which provided a test pixel selection technique which avoided excessive analyst bias.

The method employed a line-column grid which was overlaid on the MSS data using the COMTAL image display (see Figs. 4.7 and 4.8). The use of such a grid constituted a systematic sample based on line-column coordinates, with sampling intervals of approximately 180 meters in the across-track dimension and approximately 450 meters in the along-track dimension. Since the variables being sampled (i.e., cover class and the assigned label) would not vary systematically with respect to the MSS line-column coordinate relative to the sampling interval, the estimates for the mean and variance provided by such a systematic sample could be considered to be unbiased (see Cochran, 1963; especially pages 206-230). The grid was constructed such that candidate pixels located by the grid were mapped precisely between the different spatial resolutions. This provided a means of developing test points for all spatial resolutions simultaneously and avoided any identifications of test pixels in one resolution from involving more than one pixel in a lower resolution. This was achieved using the smallest grid spacing which was integer divisible by the number of original data pixels averaged to compute the data values for each resolution (i.e., in the across-track dimension the number of pixels averaged

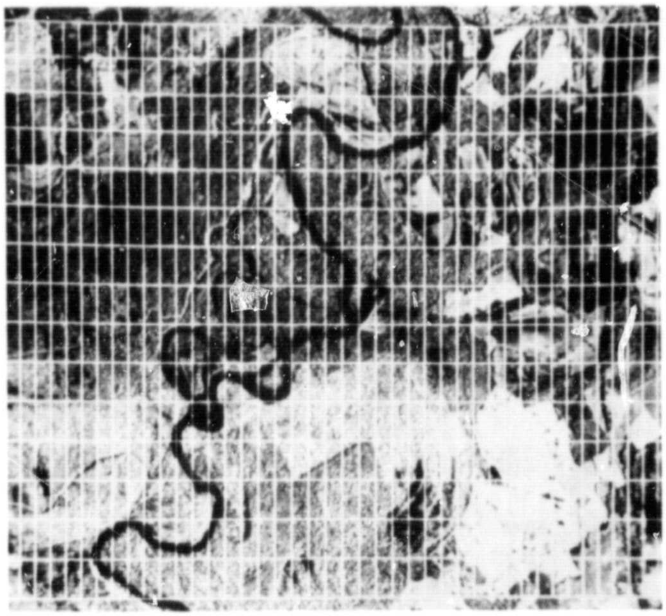

Figure 4.7. A COMTAL Vision/One image of a portion of the flight line, overlaid with the computer-defined grid used to locate and evaluate test fields.

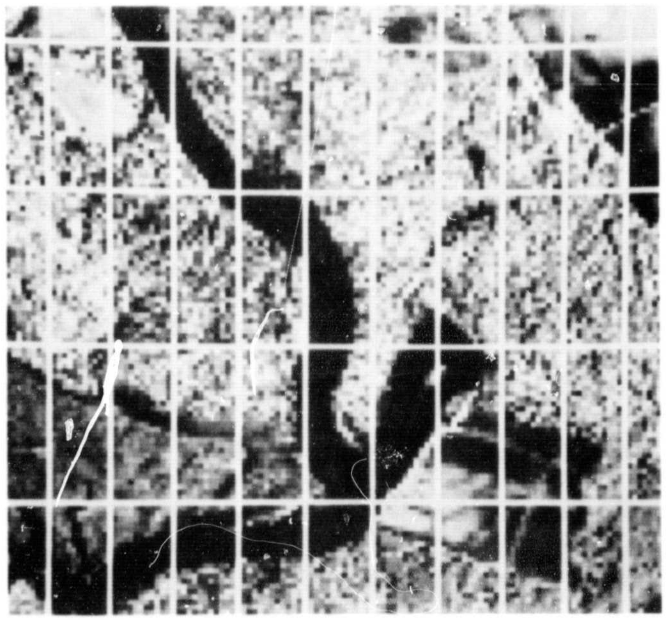

Figure 4.8. A magnification of a portion of the same image shown in Figure 4.7. Magnification to this scale was used for most of the interpretation and identification of test fields.

together were 2, 3, and 4; therefore, the smallest number for which each resolution provides an integer quotient is 12). In the along-track dimension the number of pixels averaged together were 2, 3, and 5, resulting in 30 being the smallest value with an integer quotient. The grid spacing was therefore 12 columns by 30 lines. A FORTRAN program (GRID.FTN) was modified to generate the grid for display on the COMTAL. The areas specified by the grid and associated with each resolution (the "candidate test pixels") were identified using channels 3, 4, and 5 of the 15 meter spatial resolution data and the 1:40,000 color infrared aerial photographs. Only those candidate test pixels which contained a single cover class, and which the analyst could locate and identify with a high level of confidence, were recorded as suitable test pixels. The test pixels were then mapped into the MIST coordinates of each resolution.

The grid spacing used provided 1428 possible test pixels for each flight line. In the context of the anticipated frequency at which candidate test pixels would fail the inclusion criteria, this candidate test pixel sample size was considered sufficient to provide sensitive tests for classification accuracy comparisons. A total of 523 test pixels were found to be acceptable.

3. Results of Spatial Resolution Evaluation

The first results to be discussed are based upon the training data rather than the test data set. The reasons for this are that classification accuracy estimates based on training field pixels provides a "first look" at expected classification performance. High classification accuracies of the training field pixels indicates that the spectral classes are generally:

1) statistically separable,
2) represent no more than one cover class, and
3) correspond to "natural" regions of concentration, in the measurement space, associated with the spectral characteristics of each of the cover classes in the training fields.

The classification results for the training data set are summarized in Table 4.4 by cover class group and for each of the spatial resolutions. All seven channels of data were used in these classifications. In order to evaluate the significance of possible differences in classification performance as a function of spatial resolution, a technique had to be defined which would adequately take into account the fact that there are different numbers of pixels involved for each of the four spatial resolutions for each of the different cover types. This was accomplished through the use of the harmonic mean, which is a weighted average, where the weight is proportional to the inverse of the relative magnitude of each element included in the average. The harmonic mean is, therefore, a mean value of lower magnitude than the arithmetic mean in every case where the elements are not equal (the harmonic mean equals the arithmetic mean where the elements are equal). The harmonic mean is regarded as more appropriate than the arithmetic mean for estimating a common variance among factor levels (e.g., each resolution) sampled at different intensities, since the lowest sampling intensity has the greatest weight in determining the mean.

The harmonic mean is computed by:

$$HM = m / \sum_{r=1}^{m} \frac{1}{n_r}$$

where:

HM = harmonic mean

m = the number of elements included in the mean.

n_r = the number of pixels sampled in computing the proportion correctly classified using the r(th) spatial resolution.

Table 4.4. Statistical Evaluation of Classification Performances by Cover Class for each Spatial Resolution (Training Field Pixels, Per-Point GML Classifier, 7 Wavebands of TMS Data).†

	Spatial Resolution				
Cover Class	15 Meter	30 Meter	45 Meter	80 Meter	Harmonic Mean
Tupe	96.3[a]	98.9[a]	100.0[a]	100.0[a]	182.49
Mveg	94.7[a]	97.6[a]	99.2[a]	100.0[a]	150.64
Crop	94.8[a]	97.1[a]	98.1[a]	97.3[a]	771.28
Past	93.2[a]	95.6[a]	96.6[a]	97.4[a]	503.43
Soil	94.9[a]	95.7[a]	96.7[a]	96.6[a]	1019.80
Pihd	83.7[a]	89.8[b]	91.6[b]	95.1[b]	146.22
Hdwd	82.5[a]	88.5[b]	91.2[c]	93.3[d]	2092.56
Ccut	79.3[a]	87.0[b]	89.7[c]	92.4[d]	2297.24
Sghd	72.9[a]	85.1[b]	91.3[c]	96.3[d]	1183.66
Pine	72.1[a]	81.1[b]	82.9[b]	95.5[c]	420.12
Watr	79.1[ab]	74.8[a]	79.3[ab]	82.9[b]	232.17

†Dissimilar superscripts within each particular cover class denotes a significant difference at the $\alpha = 0.10$ level of confidence based on the Newman-Keuls' range test conducted on the arcsin transformed proportions. The proportions are the relative rates of omission in classification.

In Table 4.4, as indicated, dissimilar superscripts within each particular cover class denote a significant difference between the various spatial resolutions at the $\alpha = 0.10$ confidence level.

The PCC (Percent Correct Classification) levels achieved with data of each spatial resolution were not statistically different for water tupelo, marsh vegetation, crop, pasture, or bare soil. The PCC levels achieved with data of the different resolutions were statistically different for old age hardwood, second growth hardwood, clearcut, and in some cases, for pine and pine-hardwood mix.

The irregular classification accuracies associated with the water cover class are believed to be due to the inclusion of the inundated surface mining areas as water. These areas are borrow pits which contain ridges of spoil, and the older spoil surfaces are covered with vegetation. The pixels corresponding to these areas are consequently composite measurements of the spatially weighted irradiances associated with each of the ground cover materials actually present. Thus, varying levels of "contamination" of the spectral characteristics of water with those of another cover class, is believed to be the factor responsible for the low classification accuracies achieved for water. The fact that nearly all of the misclassified water pixels were classified as a spectral class representing clearcut areas of inundated soil with standing vegetation tends to confirm the above scenario. It is of interest, however, that classifications conducted with 80 meter spatial resolution data appear to be more robust in the context of these levels of contamination.

The greatest changes in PCC with respect to spatial resolution occur with the forest cover classes. The differences in PCC among all spatial resolutions were found to be significant at the $\alpha = 0.10$ confidence level for the old age hardwood, clearcut, second growth hardwood, and pine cover classes. Classification accuracy for these forest cover classes increases with decreasing spatial resolution. While the pine-hardwood mix cover class ranged from 83.7 to 95.9 percent correct classification with 15 meter and 80 meter spatial resolution data, respectively, these differences were not found to be significant at the $\alpha = 0.10$ level of confidence. The low change in PCC with respect to resolution for water tupelo as compared to that associated with other forest cover classes is probably due to the very distinct spectral and spatial characteristics of the water tupelo.

The results shown in Table 4.4 are perhaps more easily seen in Figure 4.9, which shows a response surface for each of the individual cover classes for each of the four resolutions tested. As shown by this response surface, for most of the forest cover types, classification performance tends to increase rather dramatically with a decreased or larger spatial resolution. On the other hand, mixed crop, pasture, mixed vegetation, soil, and tupelo have very high classification performances at all four spatial resolutions. (In considering the high classification performances shown here, one must keep in mind that these results are for the training data only.) These results indicate that agricultural cover types may not be significantly impacted by the higher spatial resolution of Thematic Mapper data, but the classification performance achieved for forest cover types using per-point classification algorithms may be significantly (and adversely) affected by the higher spatial resolution of Thematic Mapper type data.

Figure 4.10 illustrates the overall classification accuracies achieved with the per-point GML classifier using data of each of the four spatial resolutions. The differences between the overall classification accuracies achieved with the data of <u>each</u> spatial resolution were found to be significant

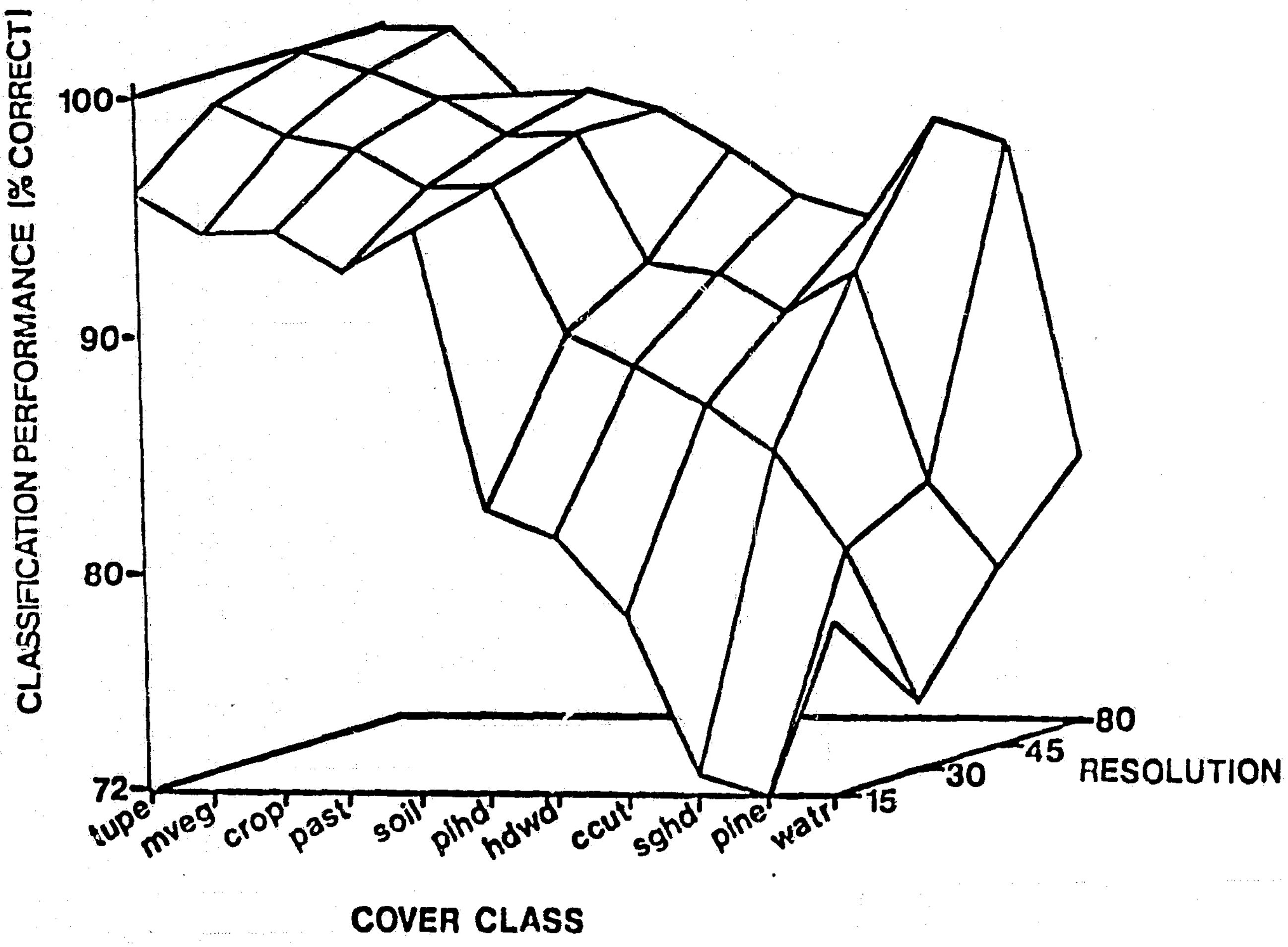

Figure 4.9. Response Surface of Percent Correct Classification by Cover Class, for each Spatial Resolution (Training Field Pixels, Per-Point GML Classifier).

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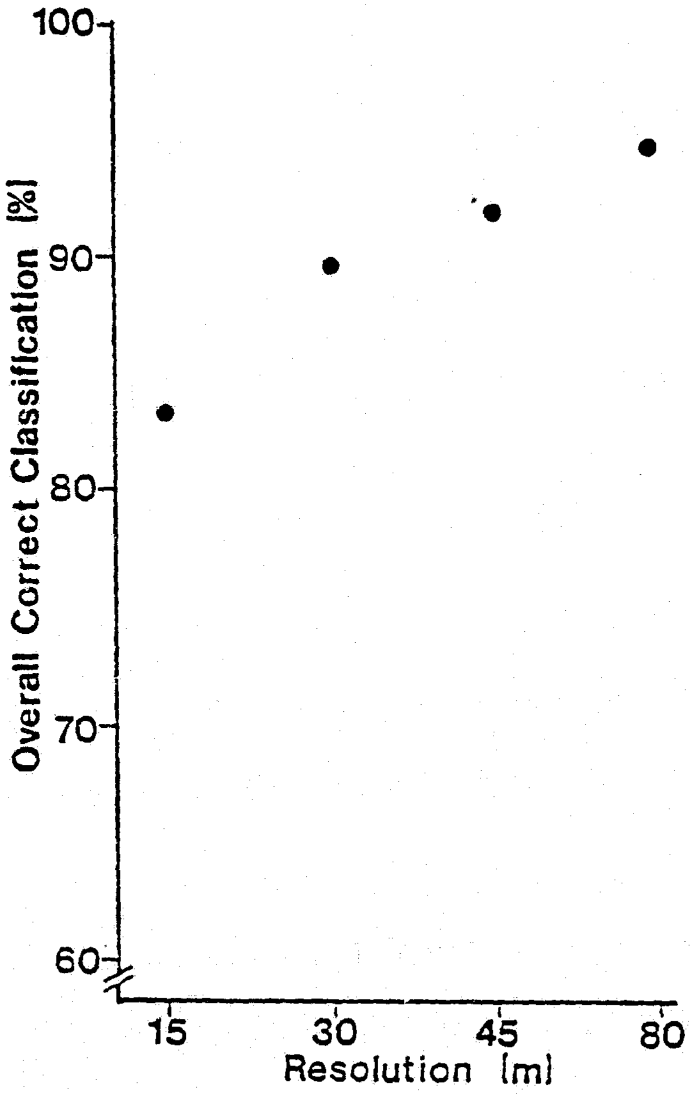

Figure 4.10. Overall Percent Correct Classification of Training Field Pixels by Spatial Resolution (Per-Point GML Classifier).

at the $\alpha = 0.10$ confidence level.[1/] This figure represents one of the key results of this project in that it clearly shows that overall percent correct classification (PCC) tends to decrease with improved spatial resolution. That is, as the size of the area on the ground corresponding to a single pixel increases, overall classification accuracy is expected to increase.

Further evaluation of the data for the different spatial resolutions indicated that the spectral variability from among adjacent pixels was much higher with the higher spatial resolution data sets. Such variation in spectral response level is clearly shown in Figure 4.11, which depicts the variation in spectral response for a single scan line in each of the spatial resolution data sets. These graphs provide some insight as to why the classification performance at the 15 meter spatial resolution was sometimes much poorer than at the Landsat spatial resolution. At the 15 meter spatial resolution, pixels for a given cover type tend to have so much spectral variability that many pixels could be spectrally similar to a completely different cover type. However, at the Landsat spatial resolution, the texture in the data tends to be averaged out within a particular pixel and the reflectance for that pixel is a representation of the overall spectral response within the pixel area. This overall or averaged spectral response is often sufficiently different for different cover types that pattern recognition algorithms can be used to effectively differentiate between the cover types involved. For example, the spectral response of Landsat resolution pixels of hardwood is sufficiently different from pine to allow effective differentiation, whereas at the 15 m spatial resolution, some pixels within the

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[1/]This test for significant differences between levels of percent correct classification used the Newman-Keuls' range test employing the arcsin transformation of the percent of correctly classified pixels.

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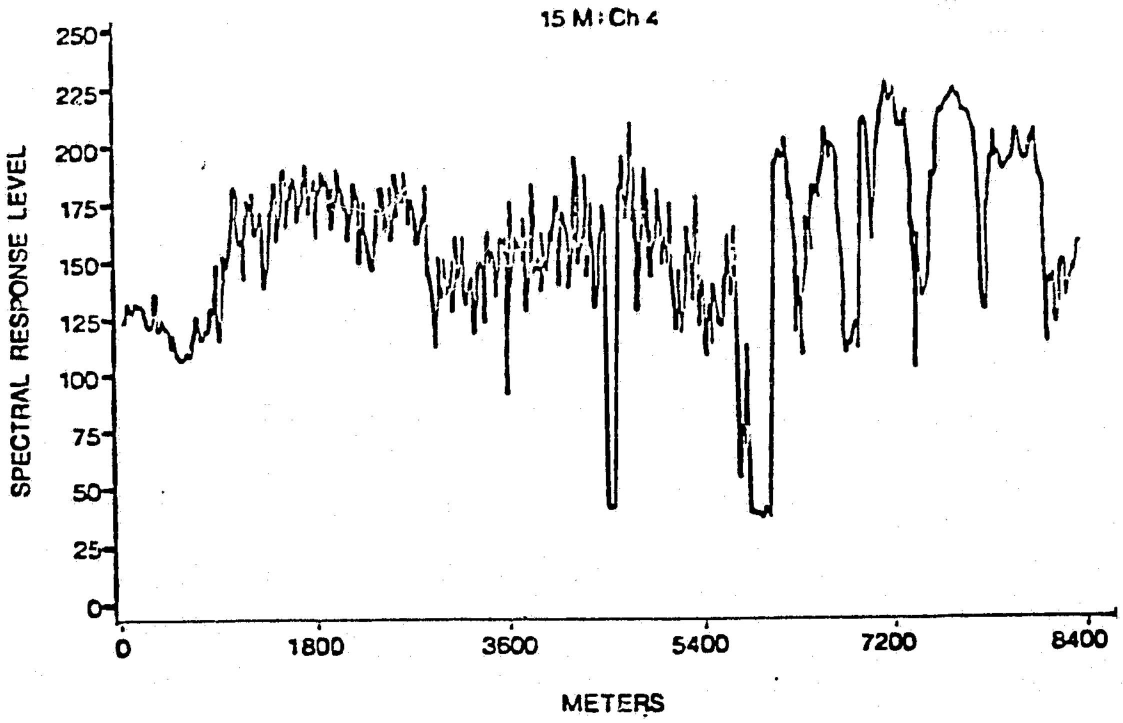

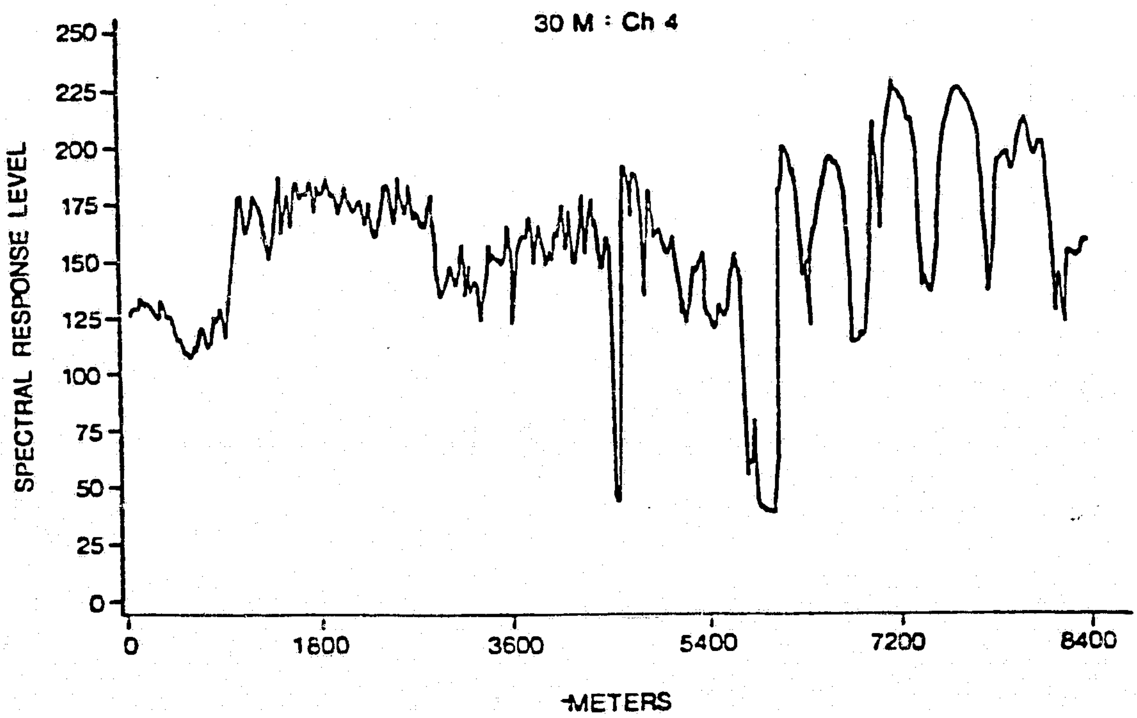

Figure 4.11. Variation in spectral response level with respect to distance in the across-track dimension for 15, 30, 45, and 60 meter sampling intervals.

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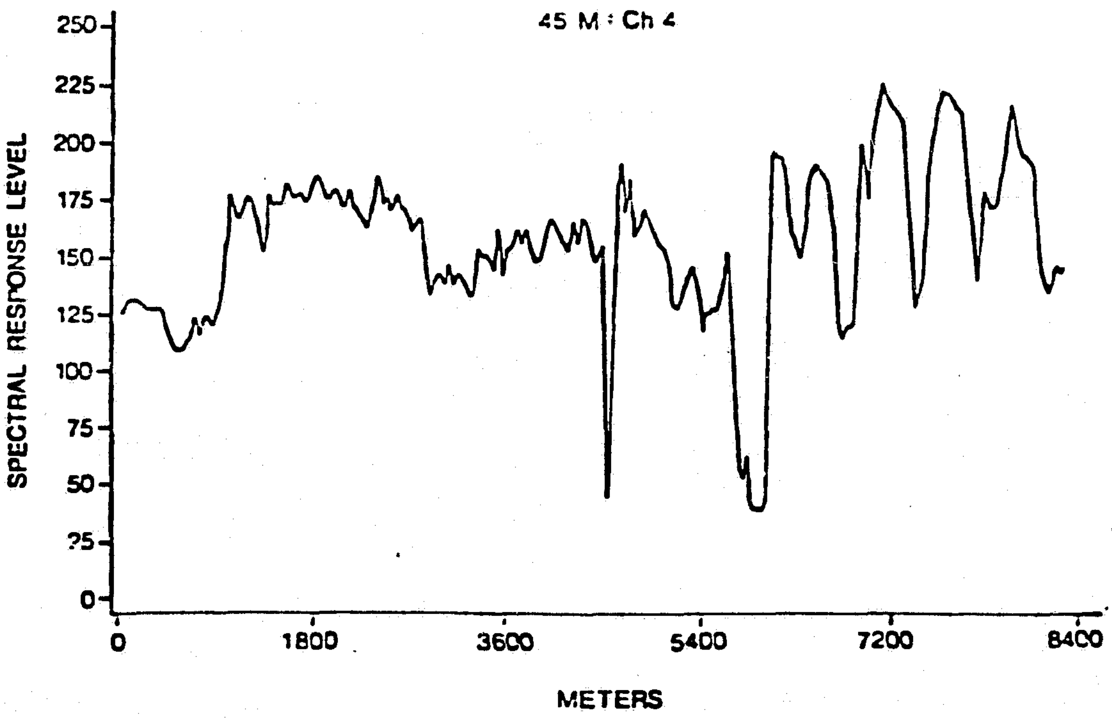

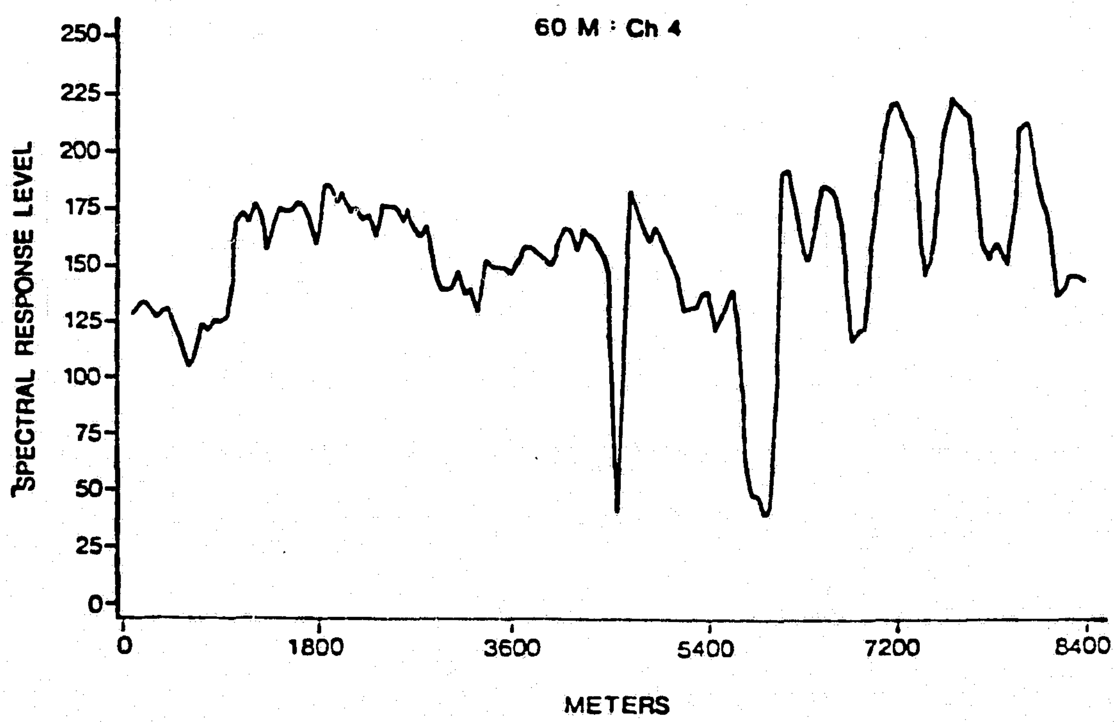

Figure 4.11, Continued.

hardwood area may actually fall partially on a shadow area between two tree crowns, possibly resulting in a spectral response similar to that of illuminated pine crowns. In such a case, this pixel within the hardwood forest area probably would be misclassified as pine. Thus, due to the greater spectral variability found among the individual pixels in the higher resolution data, many pixels are misclassified, particularly in the areas of forest cover (where spectral variability is higher than in the agricultural cover types).

The effect of spatial resolution on overall performance and on classification of the various cover types was next evaluated using the test data set. Again, all seven wavebands were used for the classification.

The overall PCC based on test pixels achieved using the "per-point" GML classifier with data of each spatial resolution are illustrated in Figure 4.12. The differences between the PCC levels achieved with data of each spatial resolution were not found to be significant at the $\alpha = 0.10$ level of confidence. The magnitude of the differences between classification accuracies achieved for training pixels and test pixels is much larger than the magnitude of the differences between PCC levels achieved for data of each spatial resolution. This would indicate that the degree to which the training classes represent the entire area to be classified is a more important determinant of classification accuracy than is the resolution of the data with which the classifications are conducted. However, the training field pixels are considered to provide a more sensitive estimate of the comparative PCC levels achieved due to either spatial resolution of the data or the classifier employed, since the factors affecting the outcome are more nearly restricted to the "resolution" factor, or the "classifier" factor, than when test pixels are used to conduct the comparison.

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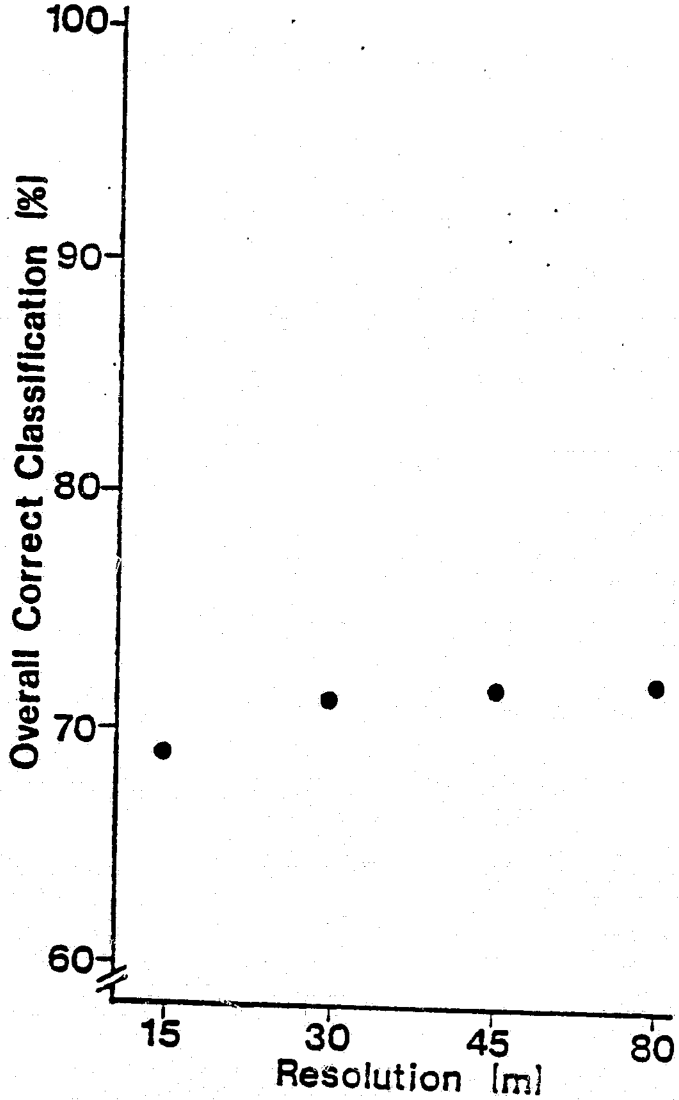

Figure 4.12. Overall percent correct classification obtained using data of four different spatial resolutions, based on test pixels.

Table 4.5 provides a summary of the statistical evaluation of the differences between data of each spatial resolution for each cover class. As indicated, when the evaluation is based on test pixels, only the PCC obtained for a subset of the cover classes characterized by large levels of spectral variability across adjacent pixels (i.e., old-age hardwood and clearcut areas) are significantly different at a 0.10 α-level. The relatively small numbers of test pixels for some cover types, especially at the larger spatial resolutions, and the large differences in classification performance between the training data set and the test data set would suggest that the test data set was not a sufficiently large sample in this case. Since the estimate of the variance of the transformed proportions is a constant, inversely proportional to the number of test pixels, the sensitivity to "real" differences between PCC is directly proportional to the square root of the number of text pixels. The estimation of PCC for the area classified is caught in the quandary of including a sufficiently large number of pixels to provide a sensitive test for "real" differences, and providing a sampling technique which assures that each test pixel satisfies the "sample" criteria. Thus, further evaluation of techniques for defining a test data set using appropriate statistical sampling procedures was necessary.

Although these test data results were not as forceful as the results obtained with the training data set, the same trends are present in both results. Since the training data represent relatively large numbers of pixels of each cover type, it is thought that for the purpose of evaluating the effect of different spatial resolutions on classification of known cover types, both the test and training data sets provide a reasonable basis for arriving at the following conclusions:

1. The use of successively <u>higher</u> spatial resolution data resulted in <u>lower overall</u> classification accuracies when classifications were conducted with a "per-point" GML classifier.

Table 4.5. Statistical Evaluation of Percent Correct Classification Performance by Cover Class for each Spatial Resolution (Test Pixels, Per-Point GML Classifier).†

Cover Class	Spatial Resolution 15 Meter	30 Meter	45 Meter	80 Meter	Harmonic Mean
Tupe	66.7[a]	55.6[a]	55.6[a]	66.7[a]	9.0
Mveg	21.1[a]	26.3[a]	31.6[a]	31.6[a]	19.0
Crop	69.7[a]	78.8[a]	84.8[a]	82.1[a]	31.86
Past	86.7[a]	92.9[a]	92.3[a]	100.0[a]	13.52
Soil	87.5[a]	85.9[a]	81.7[a]	86.9[a]	62.97
Pihd	29.0[a]	35.5[a]	25.8[a]	22.6[a]	31.00
Hdwd	72.4[a]	77.6[ab]	81.4[b]	81.4[b]	156.00
Ccut	77.5[a]	76.1[a]	81.7[ab]	88.4[b]	70.59
Sghd	66.7[a]	72.4[a]	69.4[a]	65.5[a]	121.49
Pine	36.4[a]	27.3[a]	18.2[a]	36.4[a]	11.00

†Dissimilar superscripts within each particular cover class denotes a significant difference at the $\alpha = 0.10$ level of confidence based on the Newman-Keuls' range test conducted on the arcsin transformed proportions. The proportions are the relative rates of omission in classification.

2. Higher classification accuracies were achieved with the "per-point" classifier using 60 x 75 meter (as opposed to higher) spatial resolution data in cover classes associated with relatively high levels of spectral variability across adjacent pixels (i.e., old-age hardwood, second growth hardwood, pine forest, and clearcut areas).

3. Differences in classification accuracies achieved with data of different spatial resolution were not significant ($\alpha = 0.10$) for cover classes associated with relatively low levels of spectral variability across adjacent pixels (i.e., pasture, crops, bare soil, or marsh vegetation).

In summary, although Thematic Mapper data will undoubtedly be better than the current Landsat data from a mensurational standpoint, these preliminary results, showing a decreased classification performance with higher (e.g., smaller) spatial resolution, tend to indicate that conventional per-point classification techniques may not be effective when using higher resolution data, particularly for areas involving classification of forest cover. Thus, classification techniques such as "SECHO" (which utilizes the spatial variability in addition to the mean spectral response of an entire forest stand or agricultural field), need to be tested and refined for potential use with Thematic Mapper data.

D. Evaluation of Different Numbers and Combinations of Wavelength Bands on Classification Performance

1. Introduction

As indicated previously, a major objective of this research was to evaluate the effect of using different numbers or combinations of wavelength bands on the classification results. With Landsat data only involving a maximum of four wavelength bands, there has been a tendency on the part of many analysts to simply use all four channels in all classifications without worrying about the increase in computer time involved. However, with the advent of the Thematic Mapper on Landsat-D, it is anticipated that more concern will be expressed about the number of wavelength bands to be utilized, since the classification time involved when using a Gaussian Maximum Likelihood classifier has been shown to increase logrithmically with increasing numbers of wavelength bands, with only a slight or perhaps no corresponding increase in classification performance after the inclusion of four or five wavelength bands (Hoffer and Coggeshall, 1973; Hoffer et al., 1975). Figure 4.13 shows an excellent example of these relationships.

With Thematic Mapper data, several questions can be raised concerning the number and combination of wavelength bands to be used in a classification, including:

(a) What is the minimum number of wavelength bands needed to achieve a "satisfactory" classification result?

(b) Are certain portions of the spectrum more important than others in accurately classifying a variety of cover types?

(c) Are certain particular combinations of wavelength bands more important than others in accurately classifying a variety of cover types?

(d) Will different sub-sets of wavelength bands be needed to classify different cover types, or will a single combination of wavelength bands be adequate for all cover types?

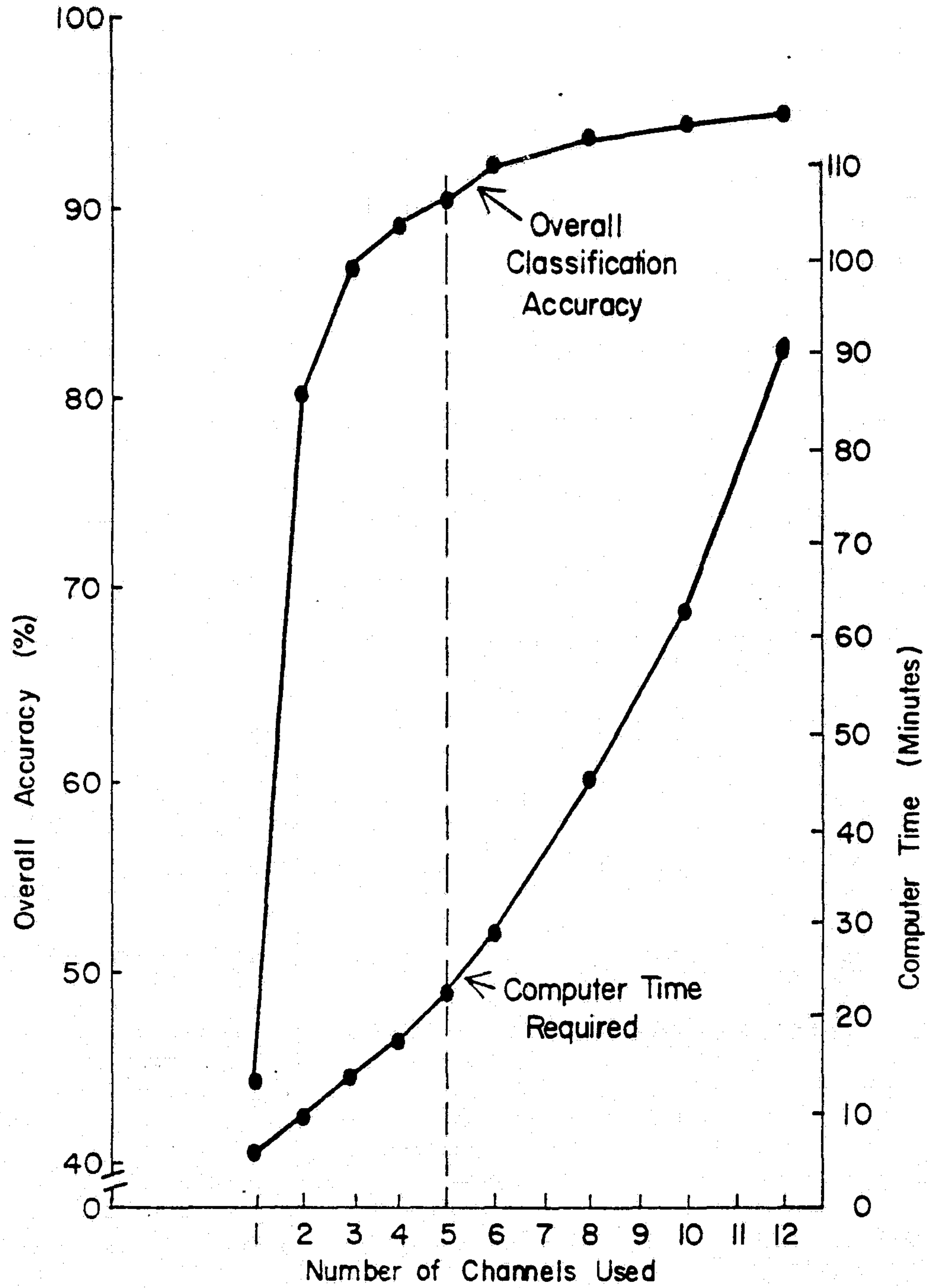

Figure 4.13. Overall classification accuracy and computer time required in relation to number of channels used. (from Coggeshall and Hoffer, 1973)

2. Transformed Divergence Evaluation Using the 1979 Training Statistics

The next major portion of this research project was directed at answering the above questions. The first phase of this work involved the 1979 data set. Supervised training fields were defined on the COMTAL Vision One/20 display, in conjunction with the color infrared photography and the field notes. Once the training fields had been identified, they were grouped according to cover class. The cover class groups of training fields were then individually clustered to resolve the cover classes into a set of spectral classes. This provided training class statistics corresponding to a set of spectral classes associated with each cover class. Clustering at this stage provided a means of defining training classes within each cover class that were based on the spectral characteristics of the data rather than some descriptive parameter that might be poorly correlated with the spectral characteristics being recorded by the scanner.

The mean vector and covariance matrix computed for each of the spectral classes define the individual statistical density associated with each respective spectral class. A measure of statistical distance between all pair-wise combinations of the spectral classes provides information on the "separability" of these spectral classes. This "separability" represents an _a priori_ estimate of the probability of correct classification (Swain, Robertson, and Wacker, 1971) for measurements provided by each channel or channel combination. Only pairs of spectral classes belonging to different cover classes are of interest, since low separability between different spectral classes of the same cover class does not affect classification accuracy.

Transformed divergence was used to compute the separability. Divergence is defined as:

$$D = \int [p_1(x) - p_2(x)] \, \ell n \frac{p_1(x)}{p_2(x)} \, dx \qquad (1)$$

where: $p_1(x)$ = statistical density of spectral class 1

$p_2(x)$ = statistical density of spectral class 2

or computationally, for the Gaussian multivariate case:

$$D = \frac{1}{2} \operatorname{tr} [(\Sigma_1 - \Sigma_2)(\Sigma_1^{-1} - \Sigma_2^{-1})] + \frac{1}{2} \operatorname{tr} [(\Sigma_1^{-1} + \Sigma_2^{-1})(m_1 - m_2)(m_1 - m_2)^T] \tag{2}$$

where: Σ is the covariance matrix and m is the mean vector associated with the respective spectral class, and

tr (trace) is the sum of the diagonal elements.

Since divergence increases without bound as the statistical distance between the two classes increases, a saturation transform is employed, resulting in a measure (i.e., transformed divergence) which corresponds more closely with percent correct classification. After a certain level of statistical difference has been attained, virtually no confusion exists between the two class densities, and percent correct classification "saturates" toward 100%. The resulting transformed divergence is provided by:

$$TD = 2000\ [1 - \exp(-D/8)] \tag{3}$$

There are some disadvantages to the use of transformed divergence as a measure of statistical difference between class densities,[1/] but because of

* * * * * * * * * *

[1/] It should be pointed out that transformed divergence is not "metric" in multivariate normal distribution functions of non-equivalent covariance matrices (Wacker and Landgrebe, 1972). That is, a pair of class densities having non-equivalent covariance matricies yet having equal mean vectors could have a transformed divergence value of zero. Also, there is no estimate for a lower confidence limit for the regression relation between transformed divergence and percent correct classification (Swain, Robertson, and Wacker, 1971).

relative computational efficiency it is used in lieu of the alternative measures.

Transformed divergence (TD) values were computed for each pair of spectral classes representing different cover classes, for each channel and channel combination. These mean pair-wise TD-values were then sorted for each set of combinations involving the same number of channels. The seven channel combinations providing the highest mean pair-wise TD-values were obtained. Additional programs were written to generate summaries of the mean TD-values for each pair of cover classes (i.e., over all spectral classes representing the cover class pair) and each cover class (i.e., over all cover class pairs involving the j^{th} cover class; $j = 1,...,12$) for these seven channel combinations.

To define the optimum number of channels to use in a classification, the relationship between cost of misclassification and the probability of error must be determined. Otherwise there is no meaningful way to compare classification cost to classification accuracy. It can be observed from Figure 4.14 that the increase in transformed divergence (the correlate to probability of correct classification) drops off sharply after three channels, and very little is gained by using more than four channels. This result is similar to those obtained previously with the Michigan M-7, 12-channel scanner (Coggeshall and Hoffer, 1973), and the Skylab 13-channel S-192 scanner (Hoffer et al., 1975). The shape of the relationship shown in Figure 4.14 indicates that transformed divergence increases logarithmically as the combination level increases linearly.[2/] The spread of the points representing the five highest

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[2/]To simplify the following discussions, "combination level" will refer to the number of channels involved in any particular set of channel combinations.

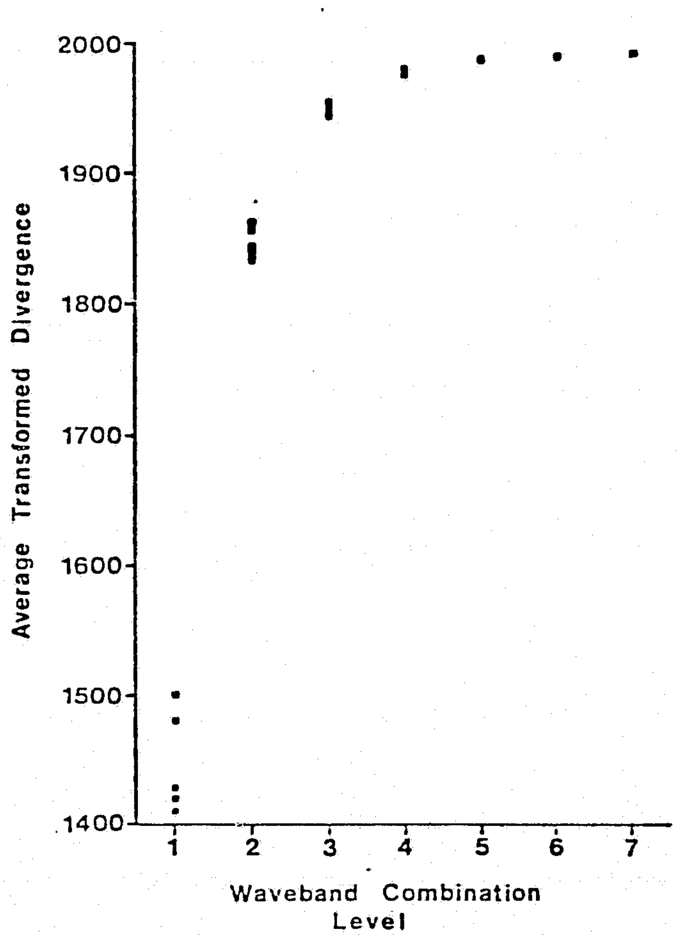

Figure 4.14. Averaged transformed divergence for the best five waveband combinations for each combination level.

ranked channel combinations for each combination level represents the difference between successively ranked averaged transformed divergence. As seen in Figure 4.14, the mean difference between successively ranked mean separabilities decreases logarithmically as the combination level increases linearly. This implies that the rank of overall mean separability as a feature selection criterion decreases in value as the number of features comprising the selected feature subset increases.

The best combined sources of information for distinguishing between various cover classes need not have as a subset the best single source of information. This is indicated in Table 4.6, which shows, for example, that the single channel having the highest mean TD-value (i.e., channel 6) is not included in the 2, 3, and 4 channel combination levels having the highest mean TD-values. By comparing Table 4.6 with Table 4.7, it can be observed that the best channel or channel combination for each combination level, on the basis of mean overall separability, is not necessarily superior on a per cover class basis.

Examination of the transformed divergence data indicated that the channel combination with the highest mean separability for a particular combination level does not necessarily provide a greater separability for all cover class pairs than channel combinations of a lower combination level, when the combination of the lower level is <u>not</u> a subset of the combination of the higher level. Examples of this relationship are: soil vs. water has a mean TD-value of 1942 in channel 6 and a mean TD-value of only 1824 in channel combination 3,4; PIHD vs. CCUT has a mean TD-value of 1835 in channel 6 and a mean TD-value of only 1641 in channel combination 3,4; PINE vs. MVEG has a mean TD-value of 1424 in channel 1 (the channel ranked third on the basis of mean overall TD-value) and the mean TD-value of 1182 in channel combination 3,4 (the number

Table 4.6. Channel combinations, ranked by overall mean TD-value for combination levels one through six.

COMBINATION LEVEL					
1	2	3	4	5	6
6	3,4	3,4,5	1,3,4,5	1,3,4,5,6	1,2,3,4,5,6
3	3,5	3,4,6	3,4,5,6	2,3,4,5,6	2,3,4,5,6,7
1	2,4	3,5,6	1,3,4,6	1,2,3,4,5	1,3,4,5,6,7
5	2,5	2,4,5	3,4,5,7	1,3,4,5,7	1,2,3,4,6,7
2	3,6	2,4,6	2,4,5,7	3,4,5,6,7	1,2,4,5,6,7
4	4,6	2,5,6	2,3,4,6	2,4,5,6,7	1,2,3,4,5,7
7	1,4	1,3,4	1,3,5,6	1,2,3,5,6	1,2,3,4,6,7

Table 4.7. Best channels and channel combinations by TD-value for each cover class. TD-value is in parentheses.

	COMBINATION LEVEL			
	1	2	3	4
soil	3(1820)	24(1941)	256(1987)	1346,2346,1356(1992)
past	6(1476)	35(1878)	345(1971)	3457(1987)
crop	3(1390)	34(1836)	345(1971)	1345(1991)
pine	2(1435)	34(1780)	346(1912)	3456(1960)
pihd	2(1580)	36(1883)	356(1982)	3456(1997)
hdwd	3(1688)	34(1881)	134(1933)	2346(1952)
sghd	3(1691)	35(1933)	346(1960)	1345,1346,2346(1972)
tupe	6(1658)	34(1896)	245,345(1979)	2457(1992)
syca	5(1753)	35(1979)	345(1994)	1345,1346,1356(1999)
ccut	6(1329)	46(1707)	356(1889)	3456(1947)
mveg	4(1270)	14(1739)	134(1941)	1345(1990)
watr	5(1853)	25(1988)	246,256(1999)	1345,1346,1356(2000)

SOIL, bare soil; PAST, pasture; CROP, row and cereal crops; PINE, pine forest; PIHD, pine-hardwood mix; HDWD, old age hardwood; SGHD, second growth hardwood; TUPE, water tupelo; SYCA, sycamore hardwood; CCUT, clearcut areas; MVEG, marsh vegetation; WATR, river water and quarry water.

one ranked channel combination of all combinations involving two channels). The same relationship holds for many other cover class pairs. Such a relationship was not found when the lower level channel combination was a subset of the higher level channel combination (as would be expected).

By increasing the combination level, the additional average separability achieved for each cover class varies greatly between cover classes and combination levels, but generally decreases logarithmically with increasing combination level. Figure 4.15 can be thought of as a "separability response surface." The apparent length of the lines connecting different combination levels of the same cover class is proportional to the added separability resulting from the information in the additional channel. Note that the greatest increase in separability due to the addition of the second channel occurs with second growth hardwood. As one would expect, the smallest increase in separability occurs with that cover class with the highest single channel separability (soil, in this case). It should be noted that the lines connecting the different cover classes are present merely to indicate relative differences of separability and in no way imply any functional relationship.

Figure 4.16 plots the maximum transformed divergence observed for <u>each</u> cover class in each combination level. This displays the maximum separability attainable for each cover class if the waveband combinations were selected on the basis of each cover class TD-value alone. As is clearly shown, the specific waveband combination resulting in each particular TD-value for any given waveband combination level is not constant over the different cover classes. In comparing Figures 4.15 and 4.16, it is apparent that the shapes of the surfaces become more and more alike as waveband combination level is increased, and are nearly identical in shape after combination level 4. This indicates that the separability by cover class provided by the best <u>overall</u>

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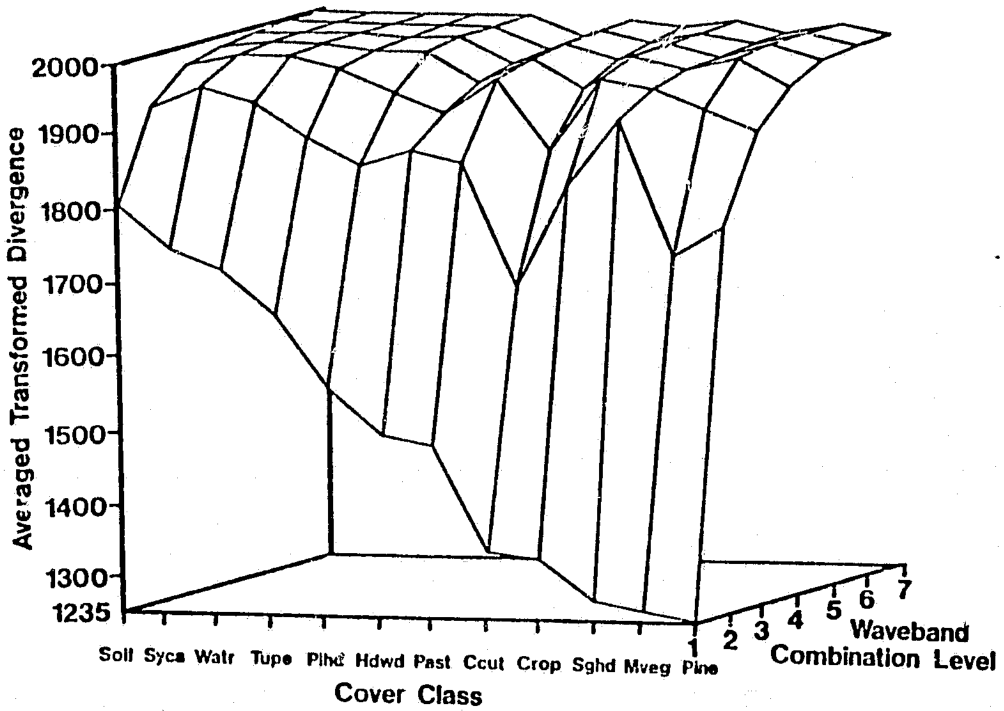

Figure 4.15. Averaged transformed divergence provided by the best overall waveband combination by waveband combination level and cover class.

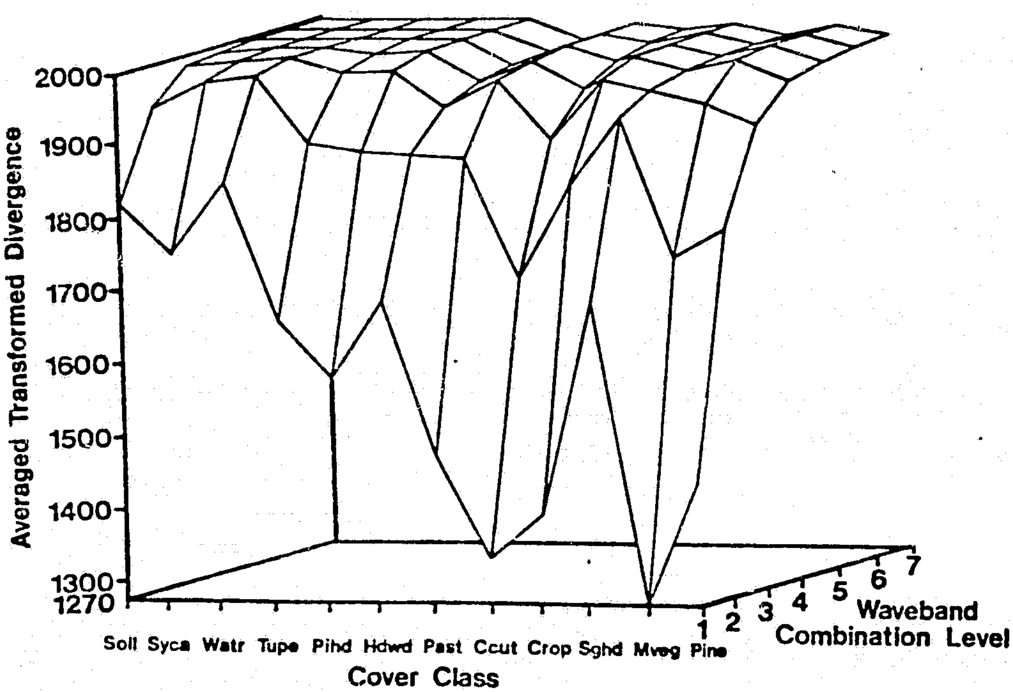

Figure 4.16. Averaged transformed divergence provided by the best waveband combination for each cover class by waveband combination level and cover class.

channel combination (Figure 4.15) is nearly identical to the separability by cover class provided by the best channel combination for each individual cover class (Figure 4.16) beyond waveband combination levels of 4. Thus, the best four waveband combination, based on overall transformed divergence, should provide very close to the maximum classification accuracy for each individual cover type. However, if one were interested only in a particular cover type, high classification accuracy probably could be achieved using less than four channels of data.

Based upon these results, therefore, one would not expect a computer-based classification employing more than four channels to provide much improvement in overall classification accuracy. The highest overall mean separability was provided by channels 1, 3, 4, and 5 (0.45-0.52, 0.63-0.69, 0.76-0.90, and 1.0-1.3 μm) — two visible and two near infrared channels. Note however, that this channel combination did not always provide the highest mean separability by cover class nor by pairs of cover classes.

It should be noted that results such as these are highly data and application dependent. A different set of cover classes, or even a subset of the cover classes, could result in other channel combinations yielding higher or lower predicted classification accuracies. For this reason, these results were further evaluated by comparing them to results obtained with a different set of training statistics developed by another analyst, which are discussed in the next section. Furthermore, the results discussed thus far have involved only predicted classification accuracies, based on the Transformed Divergence Values of the training statistics. It was therefore important to evaluate different waveband combinations using actual classification results, both for training and test data sets.

3. Effect of Different Numbers and Combinations of Wavelength Bands on Classification Results

The next phase of the investigation involved comparisons among a large number of actual classification results using both the 1979 and 1980 data sets, in which different numbers of and combinations of wavelength bands were utilized. Classification of a second data set was desired in order to evaluate the repeatability and reliability of the results obtained from the first data set. In order to eliminate as many variables as possible, only the 30 meter spatial resolution data set was used in these evaluations, and only the Gaussian Maximum Likelihood (GML) algorithm was utilized. A single set of training and test statistics were developed for the 1979 data, and another set were developed for the 1980 data. Each set of test data was then used for all waveband comparisons for the particular data set involved. Because the 1979 data had been obtained on May 2 but the 1980 data had not been obtained until August 29, there were some significant differences in the vegetative condition of the various cover types. It was thought that this might cause some differences in the results between the 1979 and 1980 data for the waveband evaluation portion of the investigation, but the two data sets would also provide some indication of the importance of the various wavebands, based upon the repeatability of the results.

a. Development of Training Statistics

For the results of this phase of the investigation to be valid, it was important that an accurate, representative set of training statistics be developed. Previous work had shown that the method used to develop training statistics for Landsat data could cause differences in classification performance by as much as 14%, based on evaluation test data (Fleming and Hoffer, 1977). In that study, the Multi-Cluster Blocks technique was found to be the best for achieving the highest overall classification performance. However, in the current study, it was important to evaluate the effectiveness of various wavelength bands and spectral regions for specific cover types, thereby indicating the need to use the "standard" supervised technique for developing the training statistics. To provide an additional evaluation of the different methods for developing training statistics, therefore, both techniques (i.e., Supervised and Multi-Cluster Blocks) were used and the results were compared.

The training classes defined for this phase of the investigation and the number of spectral classes corresponding to each cover class are shown in Table 4.8. Because the earlier work had indicated relatively small spectral differences between old-growth and second growth hardwood, these categories were grouped into a single "hardwood" category for the remainder of the investigation. Additionally, because the earlier work had resulted in only two and four training fields being defined for mixed vegetation and pine/hardwood mix, respectively, and due to the difficulty of defining additional areas of similar characteristics for use as test fields, these cover type categories were not used in the remainder of the study. Separability of the spectral classes representing the different informational classes was verified by histogram plots of the training data, and further checked using transformed divergence values. The transformed divergence values indicated that in most cases a very high separability could be achieved for most channel combinations when utilizing three or more of the seven available channels of the 1979 TMS data set (1980 had 8 channels). Some potential difficulties did show up, however, such as a relatively low separability between a spectral class of pasture and one of clearcut, but for most channel combinations of four or more channels, even this confusion did not appear to be significant.

Table 4.8. Description of the cover classes and number of spectral classes within each cover class (1979 TMS data, waveband evaluation study).

Cover Class	Number of Spectral Classes	Description of Cover Class
Tupe	2	Water tupelo; generally restricted to remnants of narrow ox-bow lakes and other areas of inundated soils.
Crop	2	Row crops and small grain crops in varying stages of size, canopy density and maturity.
Past	4	Pasture and old fields; plant cover varies from healthy, improved pasture grasses to senescent forbs and invader species.
Soil	4	Bare soil areas associated with agricultural activities; varies in sand, clay, and organic material content as well as moisture content.
Hdwd	2	Middle to old age bottom-land hardwood; mixed species, found in stands varying from very dense to stands with large inter-crown gaps.
Ccut	6	Areas subjected to clearcut forestry practices; ground cover comprised of dry to inundated soils with varying amounts of residual or regeneration vegetation.
Pine	3	Pine forest plantations, primarily slash and loblolly; evenaged stands at various stages of maturity.
Watr	4	Water; includes the Wateree River, dark marsh water, and water associated with surface mining.

As mentioned above, in addition to the supervised training data set, a second set of training statistics were developed using the Multi-Cluster Block (MCB) technique, in which several heterogeneous blocks of data are defined and each is clustered into several (perhaps 15-25) spectral classes. The cluster maps are then compared to the aerial photos and key spectral classes identified, while others are merged or deleted, as appropriate. A "MERGE STATISTICS" program is then used to combine spectral classes from the individual cluster blocks, and a single set of training statistics representing the entire study area is generated. This second set of training statistics provided an excellent opportunity to evaluate the effect of the different techniques for developing training statistics on classifier performance.

b. Development of Test Data Sets

Four separate methods for developing test data sets were evaluated during this study — one based upon an analyst-supervised set of test fields, and the other three based upon a stratified sampling procedure incorporating a grid system with dimensions of 50 lines by 50 columns.

The supervised test data set was selected by two analysts in such a fashion as to represent all major cover types present in the study site, and to obtain test data from throughout the study site in case there were any along or across-track variations which might still have been present in the data, even subsequent to the radiometric corrections applied. Table 4.9 shows the number of pixels for each cover class selected by this procedure. The major draw-back of this approach is the possibility of analyst bias which may be involved due to, perhaps, an unconscious selection of only dense, homogeneous areas of various cover types to use as test fields.

Table 4.9. Comparison among three techniques for defining a test data set using the 1979 TMS data.

	No. of Test Pixels Using Each Technique		
Cover Type	Supervised Test Fields	Grid Intersection With One Test Field	"Sample Block Test Data"
Tupelo	210	126	118
Crop	197	133	369
Pasture	124	4	350
Soil	606	261	1006
Hardwood	3032	8181	7269
Clearcut	537	163	370
Pine	577	1299	775
Water	164	28	300
Total	5447	10195	10557
Percent of Total Flight Line Area	2.4%	4.5%	4.7%

A procedure was therefore developed to define a set of test fields in the manner which was essentially free of possible bias introduced by the analyst doing the selection. This procedure involved a grid system having a spacing of 50 lines and 50 columns, which was overlayed onto the TMS scanner data. Three possible methods for defining test data sets based upon use of this grid were examined.

For the 1979 data, the grid yielded 78 intersection points in the data. The first method based on the grid involved use of a single pixel as a test field at each of the intersection points. However, such a procedure would not generate a sufficiently large set of test data to provide an adequate evaluation of the classification result. In addition, previous experience had shown that precise location of a single X-Y coordinate of MSS data on aerial photos or vice versa is very difficult. For these reasons, this single pixel technique was not given further consideration.

The second method based on use of the grid involved designating a test field in the upper left corner of each grid intersection. Each test field would be as large a sample as possible of the cover type occurring at the intersection, up to a maximum of 25 lines x 25 columns. A Bausch and Lomb Zoom Transfer Scope (ZTS) was used to transfer the grid intersection locations to the aerial photos in order to identify the cover types. Details of these procedures were documented in the eighth Quarterly Progress Report (March 1 - May 31, 1981), LARS Contract Report 053181. Implementation of this grid technique in the 1979 data set could have resulted in a maximum of 78 test fields, each 25 rows by 25 columns in size, or a total of 48750 pixels. This maximum or best case situation would have resulted in 27.2% of the pixels in the flightline being used as test fields. However, any test field in conflict with previously designated training fields or cluster blocks was reduced in size until the conflict was removed, and, of course, most test fields did not fall in a location where they could be designated as a full 25 x 25 pixel size. A summary of the number of pixels for test areas in each cover class that resulted from this procedure is shown in Table 4.9. As indicated, the actual number of test pixels obtained using this technique was 10195, or 4.5 percent of the total data. A significant problem with this procedure is indicated by the fact that some cover types were poorly represented in the test data set. This problem indicated a need for a different method of selecting test data in a statistically unbiased manner.

The method determined to offer the best solution to the problems previously encountered in defining test data sets again involved the 50 line x 50 column grid, and has been designated as the "Sample Block Test Data" technique. With this technique, a set of primary sample blocks, each of which was 25 x 25 pixels in size, were designated in the upper left corner of the 50 line x 50 column grid. The analyst then defined one test field for each cover type or information class present within each 25 x 25 sample block. Each test field was defined so as to include the largest possible rectangle of the cover type involved, regardless of the density, condition, or other variability of the cover type present. It was believed that this procedure precluded most of the potential analyst bias that may be present in using a straight "supervised" approach, but would provide a reasonable sample of all cover types present, with the number of pixels representing each cover type, being approximately in proportion to the area of that cover type present in the flight line. Table 4.9 shows the results of this approach for defining a test data set for the 1979 data. Each cover type appears to be reasonably well represented. However, it should be noted that because there is such a large amount of hardwood present in the study site, the hardwood cover type represents a large proportion of the test data, and therefore the overall classification results will tend to be dominated by the classification performance of the hardwood cover type.

c. Classification of the 1979 Training Data

After development of the training and test data sets, they were evaluated using a Gaussian Maximum Likelihood (GML) classification and all seven wavelength bands. The results for the training data, defined using the supervised method are shown in Table 4.10. Such high classification performance indicates that all cover types defined for the 1979 data set are indeed spectrally separable. Note that such a conclusion is all that can be obtained from such a table of training data results—such a table cannot be used as an indication of overall classification performance throughout the entire flight-line. Table 4.11 shows the training data classification results using only four wavelength bands (Channels 2, 4, 5, and 7). Use of only four bands still resulted in highly accurate classification results, thereby confirming the results shown previously in Figures 4.15 and 4.16, which were based on Transformed Divergence values of training data, and which had indicated that four wavebands should result in accurate overall classifications as well as accurate classifications of each of the individual cover types.

Classifications of the training data using the Multi-Cluster Blocks approach were obtained, but cannot be shown in tabular form because in this technique each X-Y coordinate within the cluster block is classified independently. Map printouts of the training blocks were compared to the aerial photos, and appeared to provide highly accurate classifications. However, only the results using test data sets will provide an effective comparison between training techniques. Likewise, the results using the test

Table 4.10. Training Class Performance Using All 7 Channels of 1979 TMS Data Based on Supervised Training Statistics and a GML Classifier.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	962	99.5	957	1	0	3	1	0	0	0
HARDWOOD	5052	98.9	5	4995	40	10	0	2	0	0
TUPELO	228	97.8	0	5	223	0	0	0	0	0
CLEARCUT	335	100.0	0	0	0	335	0	0	0	0
PASTURE	325	98.2	0	1	0	5	319	0	0	0
CROP	432	100.0	0	0	0	0	0	432	0	0
SOIL	344	99.7	0	0	0	1	0	0	343	0
WATER	460	99.8	0	0	0	1	0	0	0	459
TOTAL	8138		962	5002	263	355	320	434	343	459

OVERALL PERFORMANCE = 8063/8138 = 99.1

AVERAGE PERFORMANCE BY COVER CLASS = 793.8/8 = 99.2

Table 4.11. Training Class Performance Using Four Channels (2, 4, 5, & 7) of 1979 TMS Data, Based on Supervised Training Statistics and a GML Classifier.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	962	99.0	952	2	0	5	3	0	0	0
HARDWOOD	5052	98.2	11	4961	60	18	0	2	0	0
TUPELO	228	96.5	0	7	220	0	0	1	0	0
CLEARCUT	335	97.3	0	0	0	326	5	0	1	3
PASTURE	325	93.5	0	1	0	19	304	0	1	0
CROP	432	99.5	0	0	0	0	2	430	0	0
SOIL	344	98.8	0	0	0	4	0	0	340	0
WATER	460	97.8	0	0	0	10	0	0	0	450
TOTAL	8138		963	4971	280	382	314	433	342	453

OVERALL PERFORMANCE = 7983/8138 = 98.1

AVERAGE PERFORMANCE BY COVER CLASS = 780.7/8 = 96.7

data set must be used to evaluate the effectiveness of using different numbers of wavelength bands and different combinations of wavelength bands. Therefore, the remainder of the classification results for the 1979 data are based only on tabulation of the results for the test areas defined by the "Sample Block Test Data" technique, described previously.

d. Classification of the 1979 and 1980 Test Data Sets

The waveband evaluation study was rather involved, due to the large numbers of channel combinations we wished to evaluate in addition to the desired comparison between two separate sets of training statistics. Table 4.12 is a summary table showing the overall classification performance along with the wavelength bands used for the various classifications. Since two sets of training statistics were involved, the feature selection algorithm often indicated different combinations of wavebands as the "Best 2", "Best 3", etc. Thus, as shown in Table 4.12, there is considerable variation in the channels defined as the "Best n" waveband combination for the two different sets of training statistics. (This also tends to indicate the "data-dependent" nature of these results.)

A complete set of the classification performance tables (or "confusion matrices") and statistical summary tables for the waveband evaluation study are shown in Appendix A of this report. The classification results tables (Nos. 2-28) are indicated by the table numbers shown in Table 4.12. Tables A-29-36 of Appendix A contain the statistical evaluation summaries for this waveband evaluation study.

In order to provide some order in evaluating this mass of classification results, the initial phase of this discussion compares the test results based on the Supervised and MCB (Multi-Cluster Blocks) training statistics using all

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Table 4.12. Summary table of overall classification results, table location, and channel subsets of the 1979 Waveband Evaluation: GML algorithm, sample block test data.

WAVEBAND COMBINATION	1 0.45-0.52	2 0.52-0.60	3 0.63-0.69	4 0.76-0.90	5 1.00-1.30	6 1.55-1.75	7 10.4-12.5	GML Training Statistics Supervised	 MCB
"Best 2"		X			X			80.5% (Table 2)[1/]	81.5% (Table 15)
"Best 3"	X		X			X		78.4% (Table 3)	
	X		X		X				76.0% (Table 16)
"Best 4"		X		X	X		X	88.1% (Table 4)	
	X		X	X		X			86.1% (Table 17)
"Best 5"		X	X	X		X	X	88.3% (Table 5)	
	X	X	X	X		X			87.6% (Table 18)
"Best 6"	X	X		X	X	X	X	89.9% (Table 6)	
	X		X	X	X	X	X		87.4% (Table 19)
All 7	X	X	X	X	X	X	X	90.7% (Table 7)	88.7% (Table 20)
Visible	X	X	X					81.0% (Table 8)	72.2% (Table 21)
Reflective IR				X	X	X		71.9% (Table 9)	64.6% (Table 22)
"Best 3 minus Thermal IR"	X		X			X		78.4% (Table 3)	
	X		X		X				76.0% (Table 16)
"Best 3 minus Middle IR"			X	X	X			85.4% (Table 10)	
	X		X		X				76.0% (Table 16)
"Best 3 minus Near IR"	X		X			X		78.4% (Table 3)	
		X	X			X			82.1% (Table 23)
"Best 3 minus Reflective IR"	X	X	X					81.0% (Table 8)	
	X	X					X		64.3% (Table 24)
Simulated Landsat		X	X	X	X			88.9% (Table 12)	87.8% (Table 26)
Four channel subsets with one channel from each wavelength region			X		X	X	X	83.4% (Table 13)	85.3% (Table 27)
		X		X		X	X	87.0% (Table 14)	86.4% (Table 28)

[1/] Table numbers refer to the classification performance tables in Appendix A of this report.

seven channels of the 1979 TMS data. It was thought that this would provide a "base-line" set of test results against which all other channel combination sub-sets could be compared, and would also provide an initial basis for comparing the two methods of developing training statistics. The remainder of the discussion on waveband evaluation phase of this study is divided into several sections as follows:

(a) Comparison of the classification results obtained with different numbers of wavelength bands (i.e., the "Best" 2 through 7 bands).

(b) Comparison of different combinations of three wavelength bands, based on the 1979 test data set.

(c) Comparison of different combinations of four wavelength bands, based on the 1979 test data set.

(d) Evaluation of the classification results for the 1980 test data set, using all eight and the "best 4" wavelength bands.

Tables 4.13 and 4.14 show the results of classifying the 1979 test data using all seven wavelength bands, based on the Supervised training statistics and the Multi-Cluster Blocks training statistics, respectively. Since both tables are based on all seven wavelength bands, they represent the best possible classification accuracy one could expect using this data set and these sets of training statistics. Because these tables are based on a statistically defined set of test data, they can be considered to be representative of the classification performance throughout the entire flight line area.[1/]

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[1/]Conventionally, results are evaluated only on the basis of the relative rate of omission. Instances of omission are the non-diagonal row elements of the error matrix. Omission is of primary interest to those concerned with the likelihood of an area "known" to be of the i(th) cover class being classified as some other cover class. The commission error is equally a part of the error frequency associated with a classification. Commission error is represented by the non-diagonal column elements of the error matrix. This index of error is of interest to those concerned with the likelihood of an area being classified

Table 4.13. Waveband Evaluation Classification Results Using All 7 Channels. (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	95.0	736	2	0	11	25	0	1	0
HARDWOOD	7269	93.2	126	6774	113	128	127	0	0	1
TUPELO	118	67.8	0	19	80	16	1	2	0	0
CLEARCUT	370	64.9	80	0	0	240	19	0	31	0
PASTURE	350	83.4	0	3	0	36	292	19	0	0
CROP	369	81.0	0	0	0	1	69	299	0	0
SOIL	1006	90.6	0	1	0	64	23	0	911	7
WATER	300	81.7	0	5	0	47	0	0	3	245
TOTAL	10557		942	6804	193	543	556	320	946	253

OVERALL PERFORMANCE = 9577/10,557 = 90.7%

AVERAGE PERFORMANCE BY COVER CLASS = 657.6/8 = 82.2%

Table 4.14. Waveband Evaluation Classification Results Using All 7 Channels. (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	93.3	723	90	25	8	10	0	0	0
HARDWOOD	7269	91.1	367	6621	96	16	100	69	0	0
TUPELO	118	83.9	6	12	99	0	1	0	0	0
CLEARCUT	370	45.7	103	0	0	169	15	1	82	0
PASTURE	350	61.4	31	6	0	9	215	75	14	0
CROP	369	98.6	2	1	0	0	1	364	1	0
SOIL	1006	90.8	14	1	0	15	12	51	913	0
WATER	300	86.7	6	2	0	25	0	2	5	260
TOTAL	10557		1252	6652	220	242	354	562	1015	260

OVERALL PERFORMANCE = 9364/10,557 = 88.7%

AVERAGE PERFORMANCE BY COVER CLASS = 651.5/8 = 81.4%

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As can be seen, both sets of training statistics resulted in highly accurate overall classification results, although some of the individual cover classes had surprisingly low classification performance. Differences between the two sets of training statistics resulted in distinct differences in classification performance for some of the cover types, such as tupelo (67.8% vs 83.9%), clearcut (64.9% vs 45.7%), and pasture (83.4% vs 61.4%). A statistical comparison (Newman-Keuls Multiple Range Test) indicated that the overall classification performances were significantly different ($\alpha = 0.10$), and that among the individual cover types, only the pine and soil classes were not statistically different. However, because there is so much variability from one cover type to another as to which set of training statistics provided the best classification, it is not clear that either method of developing training statistics is distinctly better than the other. Some cases where the MCB approach was much better than the supervised, such as tupelo and crops, were quite surprising, and would seem to indicate that the supervised training data had not been adequately representative of the spectral characteristics of those cover types.

A comparison of classification results for the "Best n" (2 through 7) channel combinations was a key element in the waveband evaluation phase of this study. The "Best n" channel combination was based on the "Feature Selection" algorithm, which was based on a divergence algorithm, as discussed earlier.

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as the i(th) cover class when actually the area is in some other cover class. Both of these forms of misclassification constitute a legitimate error. The problem of providing a meaningful index for evaluating a classification arises when the evaluation is conducted by cover class, since the use of either measure will result in the same computed "overall" classification performance. The problem is most crucial when the two error components are poorly correlated, which is often the case. Work is needed to determine a legitimate and effective methodology for combining the two error components.

The analyst can use this divergence algorithm to define the "Best n" channel combination based on the minimum divergence between any two spectral classes, thereby helping to define a channel combination that will improve the classification performance for those spectral classes that are hardest to separate. The analyst could alternatively ask for the "Best n" channel combination based on average divergence, which would indicate the channel combination that should enable the best average classification to be obtained. After some initial evaluations of the data, it was determined that several combinations of channels often provided the same average divergence values (especially when more than three channels were involved), so throughout this phase of the research, the channel combinations used were defined on the basis of the minimum divergence values defined by the feature select processor.

Tables 4.15 and 4.16 show summaries of the results, by cover class as well as overall and average performance percentages, for the "Best 2" through the "Best 7" waveband combinations, for the Supervised and the MCB Training Statistics, respectively. (These summary figures were obtained from Tables 2-7 and 15-20 in Appendix A.) As indicated in Table 4.15, the classifications with only two or three channels were much lower in both overall and average classification performance than when more than three channels were used. It is also noteworthy that the feature selection algorithm defined a completely different set of channels (or wavelength bands) as the "Best 3" than had been defined as the "Best 2". Note also that when only two or three channels are used, the classification performance of some of the individual cover types may be considerably lower than when four or more channels are used. When more than four channels are used, the classification (for individual cover types, as well as overall and average) tends not to change very much, although the highest accuracy is generally achieved when all seven channels are utilized.

Table 4.15. "Best n" Channels Classification Results Summary for the Supervised Training Statistics (1979 TMS Data, GML Classifier, Sample Block Test Data).

Cover Class	# Test Samples	"Best 2" Channels (2,5)1/	"Best 3" Channels (1,3,6)	"Best 4" Channels (2,4,5,7)	"Best 5" Channels (2,3,4,6,7)	"Best 6" Channels (1,2,4,5,6,7)	All 7 Channels
Pine	775	87.0	94.7	91.0	93.8	93.0	95.0
Hardwood	7269	85.9	77.8	91.1	90.9	92.7	93.2
Tupelo	118	41.5	21.2	58.5	66.1	57.6	67.8
Clearcut	370	47.3	68.1	60.5	61.6	59.2	64.9
Pasture	350	44.6	62.3	82.6	80.6	85.7	83.4
Crop	369	73.7	61.5	79.7	79.9	78.9	81.0
Soil	1006	66.1	89.8	85.6	86.2	90.4	90.6
Water	300	86.3	88.0	78.7	80.7	81.3	81.7
Total	10,557						
Overall		80.5%	78.4%	88.1%	88.3%	89.9%	90.7%
Average		66.6%	70.4%	78.5%	80.0%	79.9%	82.2%

1/

Waveband Designation	Wavelength (um)	Spectral Region
1	0.45 - 0.52	Visible
2	0.52 - 0.60	Visible
3	0.63 - 0.69	Visible
4	0.76 - 0.90	Near IR
5	1.00 - 1.30	Near IR
6	2.08 - 2.35	Middle IR
7	10.4 - 12.5	Thermal IR

Table 4.16. "Best n" Channels Classification Results Summary for the MCB Training Statistics (1979 TMS Data, GML Classifier, Sample Block Test Data).

Cover Class	# Test Samples	"Best 2" Channels (2,5)[1/]	"Best 3" Channels (1,3,5)	"Best 4" Channels (1,3,4,6)	"Best 5" Channels (1,2,3,4,6)	"Best 6" Channels (1,3,4,5,6,7)	All 7 Channels
Pine	775	82.1	83.5	91.9	94.5	92.9	93.3
Hardwood	7269	86.8	76.1	88.4	89.8	89.7	91.1
Tupelo	118	24.6	48.3	62.7	81.1	78.8	83.9
Clearcut	370	20.3	30.3	41.9	44.1	43.5	45.7
Pasture	350	52.3	44.0	51.4	56.0	60.0	61.4
Crop	369	52.0	90.0	99.2	98.9	97.6	98.6
Soil	1006	91.0	92.0	91.3	91.3	89.8	90.8
Water	300	86.3	86.0	87.3	85.7	87.7	86.7
Total	10,557						
Overall		81.5%	76.0%	86.1%	87.6%	87.4%	88.7%
Average		61.9%	68.8%	76.8%	80.2%	80.0%	81.4%

[1/]

Waveband Designation	Wavelength (μm)	Spectral Region
1	0.45 - 0.52	Visible
2	0.52 - 0.60	Visible
3	0.63 - 0.69	Visible
4	0.76 - 0.90	Near IR
5	1.00 - 1.30	Near IR
6	2.08 - 2.35	Middle IR
7	10.4 - 12.5	Thermal IR

Table 4.16 shows the same trends and general results seen in Table 4.15, although the overall and average classification performances are generally lower for the equivalent number of channels. (This comparison of overall classification performances probably can be observed more easily using Table 4.12.) Table 4.16 also indicates that some individual cover types, notably tupelo, were classified considerably better when at least five channels were used.

As shown in Table 4.12 as well as in Tables 4.15 and 4.16, there appears to be no definitive combination of wavelength bands that provides a distinctively optimum classification, although there are observable differences between the two sets of training statistics. For instance, use of the Supervised training statistics resulted in the Thermal IR channel being used as one of the "Best 4", "Best 5", and "Best 6" channel combinations, whereas with the MCB training statistics, the Thermal IR channel was not included until the "Best 6" channel combination was defined.

In summary, it would appear that a combination of four channels would produce much better classification results, both overall and for the individual cover types, than when three channels or less are utilized. Furthermore, if more than four channels are used, there is no evidence to suggest that significant improvements in classification performance can be obtained. These statements can be made for both the Supervised and the MCB training statistics. Such statements also support the previous results shown in Figure 4.15 and 4.16, even though those figures were obtained using an entirely different set of training statistics.

The next phase of the waveband evaluation study involved classifications based on various combinations of three channels of data. These results are summarized in Tables 4.17 and 4.18. As shown in Table 4.17, the overall

Table 4.17. Classification Results Summary for Various Three Channel Combinations and the Supervised Training Statistics (1979 TMS Data, GML Classifier, Sample Block Test Data).

Cover Class	# Test Samples	"Best 3"; also "Best 3-Near IR (1,3,6)1/	Visible only; also "Best 3"-Refl. IR (1,2,3)	Refl. IR Channels (4,5,6)	"Best 3" - Mid. IR (3,4,5)	"Best 3" Channels by TD(Ave) (2,4,5)
Pine	775	94.7	92.1	91.2	87.1	91.2
Hardwood	7269	77.8	84.6	69.5	88.6	91.7
Tupelo	118	21.2	66.1	30.5	58.5	34.7
Clearcut	370	68.1	47.6	47.3	36.5	42.7
Pasture	350	62.3	38.0	71.7	76.0	64.0
Crop	369	61.5	65.0	69.6	74.3	71.3
Soil	1006	89.8	86.3	85.7	89.2	85.4
Water	300	88.0	63.3	84.0	87.7	85.0
Total	10,557					
Overall		78.4%	81.0%	71.9%	85.4%	86.9%
Average		70.4%	67.9%	68.7%	74.7%	70.8%

1/

Waveband Designation	Wavelength (μm)	Spectral Region
1	0.45 - 0.52	Visible
2	0.52 - 0.60	Visible
3	0.63 - 0.69	Visible
4	0.76 - 0.90	Near IR
5	1.00 - 1.30	Near IR
6	2.08 - 2.35	Middle IR
7	10.4 - 12.5	Thermal IR

Table 4.18. Classification Results Summary for Various Three Channel Combinations and the MCB Training Statistics (1979 TMS Data, GML Classifier, Sample Block Test Data).

Cover Class	# Test Samples	"Best 3" Channels (1,3,5) 1/	Visible Channels (1,2,3)	Refl. IR Channels (4,5,6)	"Best 3" - Near IR (2,3,6)	"Best 3" - Refl. IR (1,2,7)	"Best 3" Channels by TD(Ave) (3,4,7)
Pine	775	83.5	90.7	93.8	89.8	38.5	64.1
Hardwood	7269	76.1	74.9	57.0	85.1	63.5	87.9
Tupelo	118	48.3	76.3	55.9	61.0	72.9	66.1
Clearcut	370	30.3	35.4	34.6	36.8	35.4	35.7
Pasture	350	44.0	40.0	50.0	57.1	69.4	72.3
Crop	369	90.0	53.4	97.3	82.9	68.8	98.4
Soil	1006	92.0	85.3	96.4	79.2	91.0	92.9
Water	300	86.0	18.3	85.3	89.3	63.0	85.7
Total	10,557						
Overall		76.0%	72.2%	64.6%	82.1%	64.3%	84.4%
Average		68.8%	59.3%	71.3%	72.7%	62.8%	75.4%

1/

Waveband Designation	Wavelength (um)	Spectral Region
1	0.45 - 0.52	Visible
2	0.52 - 0.60	Visible
3	0.63 - 0.69	Visible
4	0.76 - 0.90	Near IR
5	1.00 - 1.30	Near IR
6	2.08 - 2.35	Middle IR
7	10.4 - 12.5	Thermal IR

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results are generally quite different, with the "Best 3" channels defined by the Average Transformed Divergence having the best overall classification for three channels. Table A-29 in Appendix A indicates that these overall classification results for different combinations of three channels are all significantly different. Table A-30 in Appendix A indicates significant differences among the various combinations of three channels for individual cover types, and shows, for example, that without at least one channel in the reflective infrared portion of the spectrum, water is poorly classified, whereas use of only the visible wavelengths enabled tupelo to be classified with much higher accuracy than with any other combination of three channels. In fact, the use of only the visible channels enabled tupelo to be classified with essentially the same accuracy as obtained when all seven channels were used. Pasture was classified very poorly when only visible channels were used but quite well when only the reflective infrared portion of the spectrum was involved. Both the visible and near infrared appear to be important in obtaining a reasonably accurate classification of hardwood with this data set and the Supervised training statistics.

When using the MCB training statistics and different combinations of three channels, the results obtained were very similar to those based on the supervised training statistics, as shown in Tables 4.18, A-31 and A-32. One notable result on Table 4.18 involves the water class, which has extremely poor accuracy unless a reflective infrared channel was used in the classification. A similar result was shown for the supervised statistics, but it was not as dramatic an example of the importance of particular wavelength regions for accurate classification of some cover types.

The fact that both sets of training statistics produced similar classification performances indicates that the results obtained are largely a function of the spectral characteristics of the various cover types rather than of the training statistics.

The next phase of the study involved analysis of various combinations of four wavelength bands. Tables 4.19 and 4.20 summarize the results obtained, based on the Supervised and the MCB Training Statistics, respectively. Tables A-33, 34, 35, and 36 in Appendix A show the four channel combinations that are significantly different. Use of four channels produced rather accurate classification results—much better than could be obtained with only three channels in general. With both sets of training statistics, the four channel combination that most closely simulates the Landsat wavebands provided the highest overall classification, perhaps in part because this waveband combination seemed to be particularly effective in classifying hardwoods, as well as tupelo, pine, and exposed soil. Thus, these results do not suggest any particular advantage to using wavebands in portions of the spectrum beyond those to which Silicon detectors (used in Multi-Linear Array systems) are sensitive, at least if the primary purpose is differentiation among, and identification of, various vegetative cover types. However, if one is dealing with vegetative stress conditions or other cover types, there may be distinct advantages to using data from the Middle Infrared or Thermal Infrared portions of the spectrum. It is simply a situation in which the condition of the various cover types and the data involved in this study do not show any clear indications that the Middle or Thermal IR portions of the spectrum are more important than the Visible and Near IR regions. However, it is noteworthy that the wavelength bands on the scanner used in this study (and on the Thematic Mapper) in the Visible and Near Infrared regions are spectrally much narrower than the channels on the Landsat MSS scanners. Therefore, the classification

Table 4.19. Classification Results Summary for Various Four Channel Combinations and the Supervised Training Statistics (1979 TMS Data, GML Classifier, Sample Block Test Data).

Cover Class	# Test Samples	"Best 4" Channels (2,4,5,7)	Simulated Landsat Channels (2,3,4,5)	Four Channel Subsets with one Channel from each Wavelength Region (3,5,6,7)	(2,4,6,7)
Pine	775	91.0 [1/]	92.6	89.5	92.3
Hardwood	7269	91.1	91.8	85.7	90.7
Tupelo	118	58.5	78.0	46.6	42.4
Clearcut	370	60.5	51.4	63.0	58.6
Pasture	350	82.6	71.1	74.9	82.3
Crop	369	79.7	79.1	73.7	71.5
Soil	1006	85.6	90.3	84.2	81.0
Water	300	78.7	86.3	86.3	81.0
Total	10,557				
Overall		88.1%	88.9%	83.4%	87.0%
Average		78.5%	80.1%	75.5%	75.0%

[1/]

Waveband Designation	Wavelength (μm)	Spectral Region
1	0.45 - 0.52	Visible
2	0.52 - 0.60	Visible
3	0.63 - 0.69	Visible
4	0.76 - 0.90	Near IR
5	1.00 - 1.30	Near IR
6	2.08 - 2.35	Middle IR
7	10.4 - 12.5	Thermal IR

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Table 4.20. Classification Results Summary for Various Four Channel Combinations and the MCB Training Statistics (1979 TMS Data, GML Classifier, Sample Block Test Data).

Cover Class	# Test Samples	"Best 4" Channels (1,3,4,6) 1/	Simulated Landsat Channels (2,3,4,5)	Four Channel Subsets with one Channel from each Wavelength Region (3,5,6,7)	(2,4,6,7)
Pine	775	91.6	94.1	93.7	92.3
Hardwood	7269	88.4	90.1	86.4	87.9
Tupelo	118	62.7	82.2	71.2	79.7
Clearcut	370	41.9	37.8	41.4	40.3
Pasture	350	51.4	51.1	67.1	69.1
Crop	369	99.2	99.2	98.1	98.1
Soil	1006	91.3	95.0	90.4	90.0
Water	300	87.3	86.3	87.3	85.3
Total	10,557				
Overall		86.1%	87.8%	85.3%	86.4%
Average		76.8%	79.5%	79.4%	80.3%

1/

Waveband Designation	Wavelength (μm)	Spectral Region
1	0.45 - 0.52	Visible
2	0.52 - 0.60	Visible
3	0.63 - 0.69	Visible
4	0.76 - 0.90	Near IR
5	1.00 - 1.30	Near IR
6	2.08 - 2.35	Middle IR
7	10.4 - 12.5	Thermal IR

accuracy seen in these results may be due, at least in part, to the spectral resolution of the data being used.

The waveband evaluation based on the 1980 data set was also conducted using both Supervised and Multicluster Blocks (MCB) training statistics. Initial classifications using all eight wavelength bands available and the "best 4" wavebands produced results that were generally similar to those obtained with the 1979 data, although the classification accuracies were generally somewhat lower. The overall classification performance based on test fields was 88.5% for all eight wavebands and 82.8% for the "best 4" wavebands (1, 2, 3, & 6), using the Supervised training statistics, whereas with the MCB training statistics the results showed 79.8% and 79.7% overall performance for all eight and the "best 4" (1, 3, 4, & 5) wavebands, respectively. The performance tables for these four classifications are shown in Appendix B, Tables 59, 62, 65, and 68. One of the most noticeable results using the 1980 data set involved the very low classification accuracies obtained for tupelo. These ranged from only 17.9% to 20.0%, even when all wavelength bands were used, and for either set of training statistics. It is interesting to note that with the Supervised training statistics, most of the misclassified tupelo pixels were being identified as regenerating hardwood whereas with the MCB training statistics the misclassified pixels were being identified as hardwood. In either case, the poor performance for tupelo is attributed to seasonal changes in the spectral characteristics of tupelo as compared to other hardwoods. Early in the growing season, the tupelo has a distinct spectral response (particularly in the visible wavelengths) that is quite different from other hardwoods, whereas later in the summer, the spectral response for tupelo is similar to that of the other hardwood cover types. This difference—or lack thereof—between tupelo and the other hardwoods in the 1979 and 1980 data sets,

C-2

respectively, could be clearly seen on the color infrared photography that had been obtained in conjunction with the TMS data.

Since the 1980 data showed generally similar results to those obtained in 1979 for the four channel and the all channel classifications, further waveband evaluation classifications were not obtained using the 1980 test data set.

The waveband evaluation results, based upon both sets of training statistics as well as both the 1979 and 1980 test data sets can be summarized as follows:

1. Use of four wavelength bands produced considerably better classification results than when only two or three wavelength bands were utilized.

2. Maximum overall classification performances were obtained when all wavelength bands were utilized.

3. The increase in overall classification performance when more than four wavelength bands were utilized was minimal, therefore, indicating that an appropriate set of four wavelength bands provides the best combination of high classification accuracy and minimal computer time.

4. Various three and four wavelength band combinations using the 1979 data set indicated the importance of both the visible and near-infrared portions of the spectrum for accurately classifying various forest and other cover types.

5. These results, which were primarily focused on differentiation of various types of healthy vegetative cover, did not indicate any particular advantage for using wavelength bands in portions of the spectrum beyond those to which Silicon detectors (used in Multi-Linear Array systems) are sensitive.

6. Different combinations of three or four wavelength bands caused significant differences in classification performance of various individual cover types, but overall classification accuracies did not provide any distinct trends indicating that certain wavelength bands were superior to others. (e.g., When using four waveband combinations, several different combinations produced similar overall classification performances.)

7. The Supervised method of developing training statistics provided slightly better overall classification results than the Multi-Cluster Blocks technique for both the 1979 and 1980 data sets. It would appear that for situations where accurate, reliable reference data (i.e., "ground truth") is available over the entire study area and for data having fine spatial resolution, the Supervised technique is

generally best. It is particularly useful for waveband evaluation studies involving different cover types.

8. Overall classification accuracies based on the "best 3" wavebands defined by the average transformed divergence values were significantly higher than those based on the "best 3" wavebands defined by the minimum transformed divergence values.

E. Comparison Among Three Classification Algorithms

The analysis results discussed thus far have primarily involved the 1979 TMS data (untransformed, 30 meter spatial resolution) and the GML (Gaussian Maximum Likelihood) classifier. The next phase of the study involved an evaluation of the results obtained from the GML classifier as compared to the L-2 Minimum Distance Classifier and the SECHO (Supervised Extraction and Classification of Homogeneous Objects) classifier. Comparisons among these three classification algorithms were again conducted using the untransformed 1979 TMS data, but in addition, the three classification algorithms were applied to the untransformed 30-meter 1980 TMS data set in order to evaluate the repeatability and reliability of the results obtained using the 1979 data. One must keep in mind, however, that the 1980 data were obtained about two months later in the growing season than the 1979 data (August 29, 1980 vs June 30, 1979), and that all eight channels of the NS-001 scanner were functioning satisfactorily when the 1980 data were obtained, whereas the 1.55-1.75 μm channel had not been functional at the time the 1979 data were obtained.

The L-2 Minimum Distance classifier is based on a relatively simple classification algorithm and is much faster than the GML classifier. The SECHO algorithm utilizes both the spectral characteristics and the spatial variability in the data in making the classification decision. In view of the results showing the decreased classification performance with smaller spatial resolution data, it was thought that the SECHO classifier might provide a distinct advantage over per-point classifiers (such as the L-2 and GML) when working with the 30-meter TMS data.

In view of the previous excellent results obtained using only four channels of data, it was decided to compare the classification algorithms using the "Best 4" wavelength bands. In addition, all seven (1979 data) or eight

(1980 data) wavelength bands would be used to obtain additional insight into the value of using all available wavelength bands as compared to a four channel subset. It was also decided to use both sets of training statistics for all comparisons as a further test of the repeatability of the results.

Table 4.21 shows a summary of all 24 classifications conducted for this phase of the research. Tables B-38-49 of Appendix B show the individual classification performance results for the 1979 data, and Tables B-50-57 show the statistical analysis results for the 1979 data. Tables B-58-69 show the classification results for the 1980 data, and Tables B-70-77 show the statistical analysis results for the 1980 data.

In examining the results of these classifications, as summarized on Table 4.21, it is apparent that in all cases, the results obtained with the L-2 classifier are considerably less accurate than those obtained with either the GML or the SECHO classifier, and that the GML results are less accurate than those obtained with the SECHO classifier. Tables B-50, 52, 54, 56, 70, 72, 74, and 76 indicate that the overall classification accuracies shown on Table 4.21 have statistically significant differences ($\alpha = 0.10$) between each of the classification algorithms for every data set combination (i.e., every combination of wavelengths and training statistics, and for both the 1979 and 1980 data)! Thus, the SECHO classifier clearly provides significantly better classification results than can be obtained with per-point classifiers.

Table 4.21 also shows that when classification results for the Supervised and Multicluster Block training statistics for the same number of channels are compared, the Supervised training statistics resulted in better classification accuracies in all cases except for the SECHO classifier and the 1979 data. These differences due to the training statistics used were greater with the L-2 classifier than with the GML or SECHO classifiers.

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Table 4.21. Summary table of overall classification results for the L2, GML and SECHO classifiers. (Untransformed 1979 and 1980 TMS data, Supervised and MCB training statistics, sample block test data).

I) 1979 Untransformed TMS Data

Training Statistics and Channel Combination	Classifier		
Supervised	L2	GML	SECHO
Best 4 (CH'S 2,4,5,7)	81.8%	88.1%	90.0%
All 7 Channels	85.3%	90.7%	91.6%
Multicluster Block			
Best 4 (CH'S 1,3,4,6)	77.4%	86.1%	90.6%
All 7 Channels	81.4%	88.7%	92.3%

II) 1980 Untransformed TMS Data

Training Statistics and Channel Combination	Classifier		
Supervised	L2	GML	SECHO
Best 4 (CH'S 1,2,3,6)	75.3%	82.8%	85.9%
All 8 Channels	77.5%	88.5%	89.6%
Multicluster Block			
Best 4 (CH'S 1,3,4,5)	67.6%	79.7%	84.6%
All 8 Channels	70.2%	79.8%	84.2%

It is also apparent in examining Table 4.21 that seven or eight channels of data did enable more accurate classification results to be obtained than when only four channels were used (except in the case of the 1980 data with the Multicluster Blocks statistics and SECHO classifier). However, in many situations, the difference in performance due to the larger number of channels used was only about 2%.

It would appear, in general, that the best overall results can be achieved using the SECHO classifier. However, the 1979 and 1980 results using the SECHO classifier do not indicate the same trends in relation to the method of developing training statistics and the number of channels involved. With the 1979 data, the MCB method for developing training statistics was best, whereas in 1980, the supervised method was best (particularly when all eight channels were used).

The statistical analysis of results for individual cover types showed that, in general, there were significant differences between the L-2 and GML and the L-2 and SECHO classifiers, but that only the hardwood cover type consistently produced significant differences between the GML and SECHO classifiers, for both the 1979 and 1980 data sets. The tupelo generally had a much lower classification performance in 1980 than was the case for the 1979 data, which we believe is due to phenological differences, with the tupelo having a rather distinct spectral characteristic in 1979 (which resulted in a rather unique magenta appearance on the color infrared photos), whereas at the time of year the 1980 data were obtained the tupelo was spectrally similar to the other hardwoods. The clearcut areas (or regenerating hardwoods) were also much more difficult to classify in the 1980 data than had been the case with the 1979 data set.

In summary, the results of the comparison among classification algorithms indicated that:

1. The L-2 Minimum Distance algorithm produced significantly less accurate classifications than were obtained using either the GML or the SECHO algorithms.

2. The SECHO algorithm consistently resulted in higher overall classification performances than were obtained with the GML algorithm, regardless of the data set or training statistics being utilized.

3. Overall classification performances of 85-90%, based on test data sets, were obtained for both the 1979 and 1980 TMS data when four or more wavelength bands were utilized in conjunction with the SECHO classifier and either the Supervised or Multi-Cluster Blocks training statistics.

4. Phenological effects caused distinct differences in spectral response for some cover types, especially tupelo, when comparing the 1979 and 1980 data.

F. Effectiveness of the Principal Components Transformation in Data Analysis

The next phase of this project involved the evaluation of the principal components transformation on classification performance. Sometimes the question has been raised as to why a "feature selection" procedure should be used to reduce the number of wavelength bands for classifying a data set, as opposed to simply using the first three or four principal components of the data. Both "feature selection" and principal components are data dimensionality reduction techniques. The advantage of the principal components transformation is that it is a very automatic procedure for reducing the dimensionality of multispectral data. However, there are various methods available for defining the statistics used to calculate the principal component transformations. This phase of the research was conducted, therefore, to evaluate the use of principal component transformations, as compared to selected wavelength bands of untransformed data, for classifying forest and other cover types, based on TMS data.

A Karhunen-Loeve or Principal Component Linear Transformation was applied to the 1979 TMS data set, using a 4% sample of pixels (every fifth line and fifth column) to calculate the statistics, including a mean vector and covariance matrix. The Karhunen-Loeve transformation then calculates the eigenvectors (transformed components) associated with this sample covariance matrix, ordered in such a way that a maximum amount of data variability is accounted for in descending magnitude along these components. One particular advantage of the K-L transformation is that it uncorrelates the data in N-dimensions, i.e., the transformed components are mutually orthogonal, so that any redundancy of information caused by interband correlations of the original channels is removed. Tables C-108 and 109 in Appendix C give the statistics of the original TMS data (sampled every 5th line and 5th column) and the resulting eigenvectors (transformed components) and eigenvalues, respectively, calculated from the covariance matrix of this sampled TMS data. The information content associated with the ordered transformed components for the 1979 K-L transformed data set is shown in the form of a bar graph in Figure 4.17. As can be seen, the first components alone contains over 50% of the variance or information content in the data, and the first three components together contain 97.8% of the variance.

A supervised set of training statistics was generated from the K-L Transformed data and the same set of 1979 sample block test areas used previously were again used in this phase of the study. The data were classified using the L2, GML, and SECHO algorithms with the first 3 and 4 then the first 4 components. Results from these classifications were compared to those obtained from the "optimum" three and four channel subsets of the original TMS data (as determined by *SEPARABILITY) and are summarized in Tables 4.22 and 4.23. Appendix C includes the classification performance tables (Tables C-80-91) as well as tables of the statistical comparisons among the results (Tables C-92-107).

In evaluating the results, it is apparent that the value of the K-L transformation is strongly influenced by the classification algorithm used, particularly when only three channels of data are involved. Table 4.22 shows that when the L-2 algorithm is applied to the data, the classification performances were better for the transformed data, as compared to the untransformed data, for all cover types except water. Table C-95 indicates that these differences were statistically significant ($\alpha = 0.10$) for all cover types except tupelo and water. However, with the GML and SECHO classifiers, use of the transformed data resulted in significantly better classification

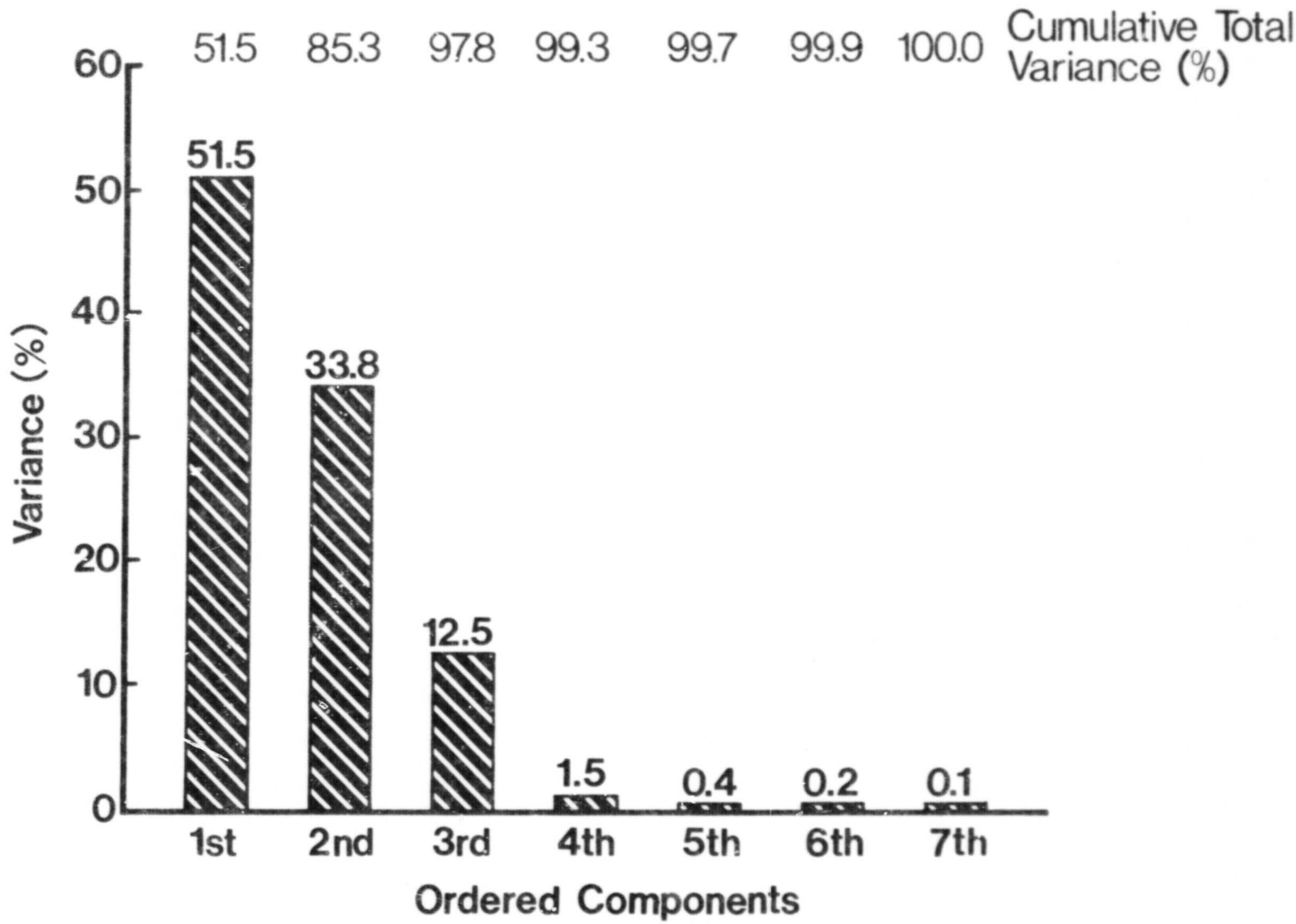

Figure 4.17. Information content or percent of total source variance accounted for by the ordered components of the 1979 K-L transformed data.

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Table 4.22. Combined comparison table of the overall and individual cover class classification performances between the untransformed TMS and the K-L transformed data for all three classifiers using "optimum" three channel feature sets.

COVER CLASS	DATA SET DESCRIPTION	CLASSIFIER L2	CLASSIFIER GML	CLASSIFIER SECHO
PINE	Untransformed TMS (CH's 1,3,6)	76.9%	94.7%	96.5%
	K-L Transformed Data (Components 1,2,3)	89.0	90.1	91.2
HDWD	Same as above	69.1	77.8	89.1
		80.9	85.9	91.3
TUPE	Same as above	45.8	21.2	22.0
		50.8	45.8	52.5
CCUT	Same as above	49.5	68.1	74.6
		61.1	47.8	50.8
PAST	Same as above	43.4	62.3	68.3
		69.4	80.0	84.9
CROP	Same as above	27.6	61.5	62.9
		89.7	87.0	87.3
SOIL	Same as above	50.4	89.8	92.0
		75.2	74.3	70.6
WATER	Same as above	88.3	88.0	81.3
		87.0	76.3	73.0
OVERALL	Same as above	65.2	78.4	86.8
		80.0	82.9	86.6

Table 4.23. Combined comparison table of the overall and individual cover class classification performances between the untransformed TMS and K-L transformed data for all three classifiers using "optimum" four channel feature sets.

COVER CLASS	DATA SET DESCRIPTION	CLASSIFIER		
		L2	GML	SECHO
PINE	Untransformed TMS (CH's 2,4,5,7)	85.5%	91.0%	92.9%
	K-L Transformed Data (Components 1,2,3,4)	89.2	92.0	92.9
HDWD	Same as above	84.0	91.1	93.7
		86.1	88.7	92.4
TUPE	Same as above	55.1	58.5	57.6
		63.6	36.4	28.8
CCUT	Same as above	68.6	60.5	58.9
		61.6	55.9	56.2
PAST	Same as above	70.9	82.6	83.1
		68.6	86.3	85.7
CROP	Same as above	88.1	79.7	81.6
		89.4	73.2	71.8
SOIL	Same as above	71.6	85.6	86.0
		75.5	69.9	69.7
WATER	Same as above	85.7	78.7	79.7
		87.0	81.0	81.0
OVERALL	Same as above	81.8	88.1	90.0
		83.8	84.6	87.0

performances for some cover types but significantly worse classifications for other cover types (see Tables C-97 and 99). Somewhat similar results were found when four channels of data were used, as shown in Table 4.23, although the differences between the untransformed and transformed performances generally are smaller, particularly with the L-2 classifier.

The overall classification performances are compared in Tables 4.24 and 4.25. Table 4.24 shows that the transformed data resulted in significantly better performance when the L-2 classifier was used for both the three and four channel situations. However, when the GML algorithm was used, the transformed data had a better overall performance for the three channel situation but the untransformed data was better with four channels. For the SECHO classifier, there was no difference for three channels and the untransformed data was best when four channels were used. Table 4.25 shows that the differences between classification algorithms generally were significant for either three or four channels and with either the untransformed or transformed data sets.

These results could be summarized as follows:

1. The K-L transformation (with 4 components) generally increased the overall classification performance of the L-2 classifier, whereas the overall classification was significantly decreased for both the GML and SECHO classifiers.

2. For individual cover types, the GML and SECHO performances tended to be rather similar—both would either increase or decrease by a similar amount for a particular cover class with a K-L transformation—whereas the L2 classifier tended to react in the opposite way; i.e., when the GML and SECHO classification cover class performances decreased with a K-L transformation, the L2 increased, and vise versa (with the exception of the CCUT and WATER categories).

3. The K-L transformation and the L-2 classifier improved all cover class performances when using three channels (i.e., components) and most cover class performances when using four channels.

4. A K-L transformation and the GML classifier improved some (i.e., half) of the cover class performances when using three channels (components), but when using four channels the classification performances were often considerably better with untransformed data.

Table 4.24. Summary table of overall classification performances comparing the untransformed TMS and the K-L transformed data sets for all three classifiers.

Data Subset: "Best 3" Channels or 1st 3 Components

Classifier	Untransformed TMS[1/] (Channels 1,3,6)	Table Location	K-L Transformed Data (Components 1,2,3)	Table Location
L2	65.2[a]	(Table 80)	80.0%[b]	(Table 83)
GML	78.4[a]	(Table 81)	82.9[b]	(Table 84)
SECHO	86.8[a]	(Table 82)	86.6[a]	(Table 85)

Data Subset: "Best 4" Channels or 1st 4 Components

Classifier	Untransformed TMS[1/] (Channels 2,4,5,7)	Table Location	K-L Transformed Data (Components 1,2,3,4)	Table Location
L2	81.8[a]	(Table 86)	83.8[b]	(Table 89)
GML	88.1[b]	(Table 87)	84.6[a]	(Table 90)
SECHO	90.0[b]	(Table 88)	87.0[a]	(Table 91)

[1/] Significantly different overall classification performances between the untransformed and the K-L transformed data sets for each classifier is indicated by a different superscript (based upon a Newman-Keuls comparison with $\alpha = 0.10$).

Table 4.25. Summary table of overall class performances for three algorithms (L2, GML, SECHO) based upon four data sets.

Data Set Description	Overall Classification Performance (%) by Classifier (and Table Location)		
	L2[1/]	GML	SECHO
3 Channels (1,3,6), Untransformed	65.2[a] (Table 80)	78.4[b] (Table 81)	86.8[c] (Table 82)
1st 3 Components, K-L Transformed	80.0[a] (Table 83)	82.9[b] (Table 84)	86.6[c] (Table 85)
4 Channels (2,4,5,7), Untransformed	81.8[a] (Table 86)	88.1[b] (Table 87)	90.0[c] (Table 88)
1st 4 Components, K-L Transformed	83.8[a] (Table 89)	84.6[a] (Table 90)	87.0[b] (Table 91)

[1/] Different superscripts between columns of the same row indicate significantly different overall classification performances between classifiers (based upon a Newman-Keuls comparison with $\alpha = 0.10$).

5. In general, it appears that for classifications using fewer number of channels (features) than is optimum for a particular data set (i.e., the <u>intrinsic dimensionality</u> of the data, which in this case is four, a K-L transformation will improve overall and most cover class performances. However, if the number of channels is equal to the intrinsic dimensionality of the data, the original untransformed data appears to provide better class separability and subsequent classification performance.

V. SYNTHETIC APERTURE RADAR (SAR) DATA ANALYSIS

A. Data Collection

The second major phase of this research project involved the analysis of the SAR data. The test site and the reference data used were the same as those involved in the TMS data analysis, and have already been described in Sections III and IVA3.

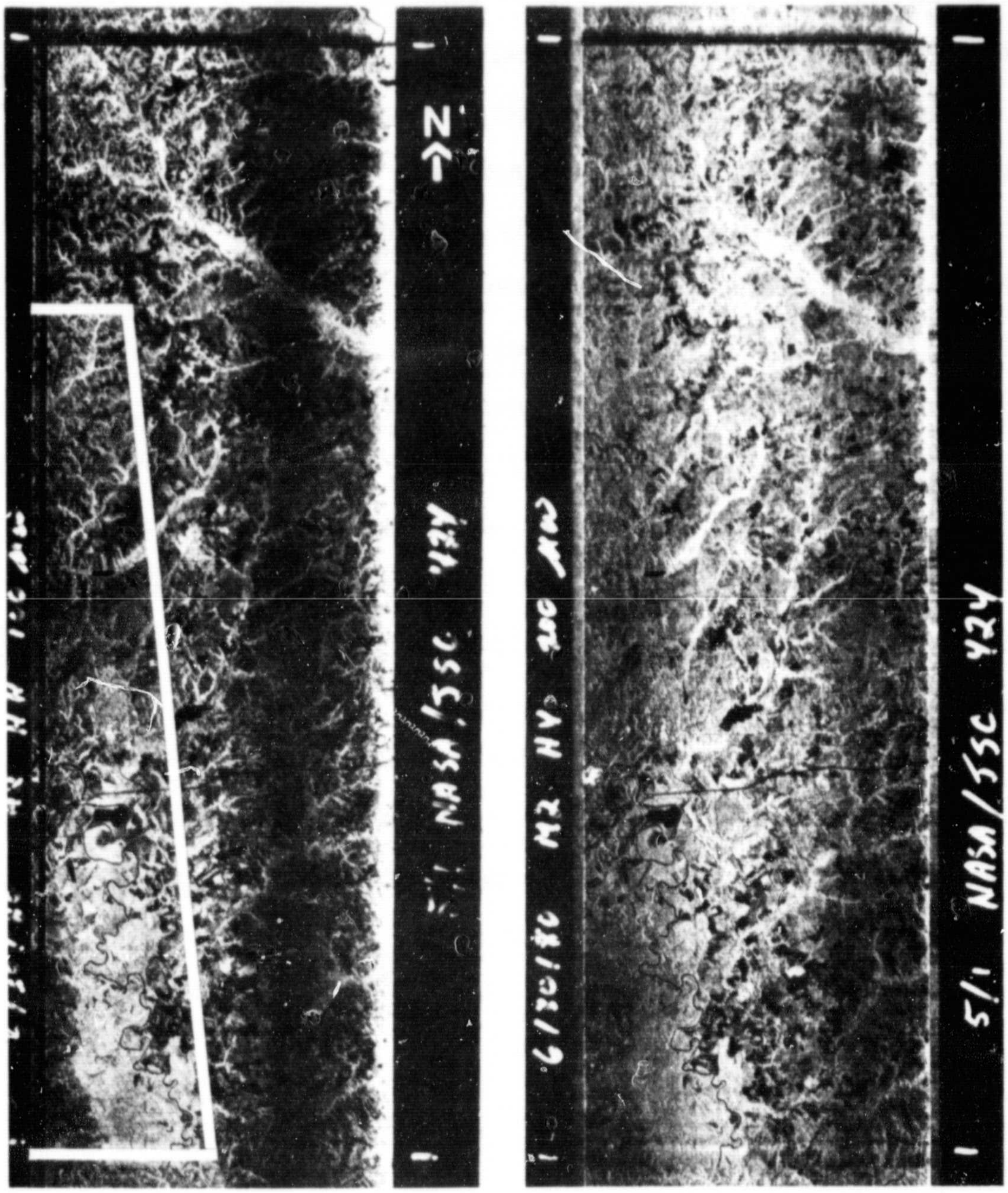
Due to the aircraft schedules and equipment difficulties, we were unsuccessful in obtaining radar data during the 1979 growing season. However, Radar Mission No. 424 was successfully flown on June 30, 1980. This was the first (and only) radar data obtained in support of this project. The sensor used was the APQ-102 side-looking synthetic aperture radar, flown in the NASA WB-57 aircraft at an average altitude of 60,200 feet MSL. Small scale (1:120,000 scale) color infrared photography was also obtained of the study site as part of this mission. The photography indicated that the area was about 30-40% covered by cumulus clouds at the time the radar data were obtained. It might be worth noting, however, that the radar data showed no indication of the presence of clouds, thereby providing an excellent example of the fact that radar does indeed provide effective penetration of clouds!

The APQ-102 side-looking radar is a fully focused synthetic aperture radar imaging system. A horizontally polarized pulse of energy of 9600 MHz ±5 MHz (i.e., X-Band) was transmitted by the radar system, and the returning energy was recorded on separate holograms as horizontally (HH) and vertically (HV) polarized responses. These holograms were then processed through an optical correlator by Goodyear Aerospace Corp. in Arizona, and the resulting images recorded on positive film, which was the format in which the data were provided by NASA to LARS.

The positive-image film was received at LARS on August 8, 1980. Black and white negatives and positive prints were then made of the radar film for handling and interpretation purposes.

Visual examination of the imagery indicated that there was a very distinct dark band running the length of the imagery that was particularly distinct on the HH polarization but also fairly noticeable on the HV polarization (see Figure 5.1). It was also found that there was very little side-lap between Flight Lines 1 and 2. This lack of side-lap, in combination with the image quality difficulties, caused the analysis of the radar data to be confined to Flight Line 1 for the area south of Camden along the Wateree River and to the upland terrain in the region north of Camden. The radar data in these areas were of satisfactory quality in both polarizations. In addition, the area south of Camden corresponded very well to the area covered by the cloud-free MSS data obtained in 1979 and again in August 1980.

Because of the problems with image quality and the lack of overlap between flight lines, detailed analysis of forest cover as a function of look angle (using the overlapping area of the two flight lines) could not be pursued with the radar data set obtained for this study.



HH HV

Figure 5.1. Radar images of Flight Line 1 for the HH and HV polarizations. The area for which MSS data were also obtained is outlined in white.

B. SAR Data Handling

1. Digitization

To convert the radar imagery into a numerical format, the positive film imagery was digitized using a microdensitometer. Both the HH and HV polarization images were digitized by the Lockheed Corporation at JSC.

The parameters for digitizing the imagery were calculated using the specifications of the radar system and an approximate scale of the imagery. The scale was determined by making several measurements between points on the radar imagery and USGS topographic maps. According to the characteristics of the system, the ground resolution for both the across track and along track resolutions was slightly less than 15 meters. This resolution performance was therefore defined as the minimum allowable dimension for a ground resolution element. Based on the 1:376,000 scale of the positive film image, it was determined that an aperture setting of 40 μm on the microdensitometer would provide a digitized pixel having a spatial dimension of 15 meters, thereby approximating the ground resolution of the SAR system. Both the sampling interval and scan line spacing were set at 40 μm to prevent any sidelap and overlap of adjacent pixels, thus providing independence between pixels. If there was any sidelap and/or overlap of the pixels, the variance between adjacent pixels would have been reduced. This would not have allowed an effective comparison among various classification algorithms, since some algorithms are more sensitive to differences in variance than others, and one of the basic assumptions of most algorithms is that the individual samples are independent.

Figure 5.1 shows the entire radar image of the test area for both the HH and HV polarizations. On the HH polarization there is a distinctive dark band running through the entire flight line, covering approximately 30 percent of the data set. The portion of the data covered by this dark band could not be used, so the final area digitized was approximately 2.7 cm x 11.7 cm, which represented an area of 6 miles by 27 miles on the ground. The 40 μm aperture setting resulted in 674 samples per line and 2897 lines of data, for a total of 1,952,578 pixels.

2. Reformatting

The digitized radar data were recorded directly onto 7-track tapes, which were later copied onto 9-track tapes in order to convert the SAR data into LARSYS format. Some problems were encountered in the quality of the digitized tapes because the same gain setting had been used to digitize both the HV and HH polarizations, thereby causing the HH data to be saturated in response. This was corrected by redigitizing the radar imagery, and in May 1981, the final set of digitized SAR data were received by LARS.

Since the HH and HV images were digitized independently, the data had to be overlaid (i.e., share the same line and column coordinates) before being combined onto a single LARSYS data tape. Initial attempts were made to overlay the entire flight swath of the two data sets using first and second order polynomials. A set of 19 control points were identified, randomly scattered throughout the data on each polarization using photo-interpretation techniques, and were checked using an image correlation program. The overall results from the models were given in terms of RMS (root mean square) error.[1/] RMS errors

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[1/]The RMS error is an unbiased estimator of σ^2 for the model (Steel and Torrie, 1980). It is defined as:

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{n} (l_i - \bar{L})^2}{n-1}}$$

where,
$\bar{L}$ = sample mean,
l_i = ith observation,
n = total number of observations.

This expression defines the accuracy of a single observation.

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less than 0.5 for both line and column coordinates were considered to give the accuracy needed for the image registration process (Smith, 1980). The results of both the first and second order polynomials did not provide acceptable RMS errors. Examination of the data indicated that a curvilinear orientation with more than one inflection point existed in the along-track direction between the data sets. This type of orientation may have developed through a combination of variables such as caused by the dual receiving antennas of the APQ-102 radar system and electronic equipment instabilities.

To compensate for the geometric variabilities, the data along the flight line was divided into four separate blocks. Over 30 potential control points were located in each block using the procedures previously mentioned. The biquadratic transformation was applied to each block and RMS errors were calculated. Table 5.1 gives the RMS errors for each block. These results indicated that blocks A1, A2, and B1 could be overlayed to the desired level of accuracy using their associated transformations. Although block B2 did not have an RMS error of less than 0.5, it was decided that the data in the block would be overlayed using its derived transformation rather than divide the block into smaller units or delete it from further analysis.[1/]

To facilitate the development of the statistics for the SAR data, the blocks of overlayed data were combined into a single data set (i.e., to simulate the original flight line). The recombining of the blocks was accomplished by visually locating overlapping points and reassigning the starting line and column locations.

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[1/]After the data was overlayed, it was determined that the registration of block B2 was extremely poor and at this point it was deleted from further analysis.

Table 5.1. Results of the biquadratic transformation for the four blocks of SAR data.

Block	Maximum Acceptable Linear Error	Overall RMS Error Line	Overall RMS Error Column	Number of Accepted Checkpoints
A1	1.5	0.484	0.487	20
A2	1.5	0.425	0.491	20
B1	1.5	0.486	0.488	21
B2	1.9	0.639	0.864	15

3. Geometric Adjustment

After the registration process, a second SAR data set was produced having a reduced spatial resolution of 30 m. The purpose of this was two-fold: 1) to match the spatial resolution of the simulated Thematic Mapper data set, and 2) to reduce the amount of speckle associated with the SAR data. The spatial resolution was degraded by averaging pairs of neighboring pixels together. Since the original digitized SAR data set had a spatial resolution of approximately 15 m, the averaging of cells of four pixels produced a degraded data set having a spatial resolution of 30 m. A separate data tape was then constructed for the 30 m SAR data set. The steps and considerations used to degrade the spatial resolution were similar to those used for the MSS data (Latty, 1981).

C. Image Interpretation Results

Various forest cover types were identified on color infrared photography taken at the same time the SAR data were obtained. The forest cover types identified on the aerial photography included old growth mixed hardwood, second growth mixed hardwood, water tupelo, and pine (primarily slash and loblolly pine). In addition, there were areas where the forest had been clearcut, as well as pasture areas, crop land, areas of exposed agricultural soil, and water features that were identified on the photography.

Following the photo interpretation, stands of the various forest and other cover types were located on both polarizations of SAR imagery. The two polarized images then were analyzed to determine if tonal and/or textural differences existed between the cover types. The tonal characteristics were determined by evaluating the relative speckle for each cover type. The tonal and/or textural differences between the HH and HV polarized images then were compared and evaluated for each cover type. An attempt was made to determine why particular differences did occur.

The initial analysis of the SAR imagery depicted a banding effect which was particularly noticable on the HH image. A much more subtle tonal variation that seemed to be related to the range angle could be observed, particularly on the HV image. Both of these effects can be observed in Figure 5.1, which shows the data for both polarizations of the entire flight line. Both effects had a significant impact on the ability of the interpreter to determine various cover types using the radar imagery alone. Both the banding and tonal variation effects were not due to any characteristics of the ground terrain, but were due strictly to variables inherent in this particular data collection and processing system. Both effects were also quite evident on several other data sets obtained at the same time over the other flight lines. It should be pointed out that the overall lack of contrast in the HV imagery may have been due to the parameters involved in obtaining and processing this particular data set and not necessarily an inherent characteristic of HV polarized imagery.

Deciduous forest cover appears to have a characteristic light tone on the HH image, whereas on the HV image these deciduous areas have a darker tone. This was most evident in the area of the alluvial plain where dense deciduous forest cover was located (see Figure 5.2). The dense deciduous forest stands located in small ravines were identified on both polarizations due to their distinctive spatial patterns (see Figure 5.3). These patterns were highlighted because of the high response given by the deciduous forest cover growing within the ravines and perhaps also highlighted in part by the slopes of the ravines _per se_ acting as angular reflectors. Due to the contrast difference between the two polarizations these patterns were more distinctive on the HH image than on the HV image.

One of the most distinct differences observed in the imagery was a difference between deciduous and coniferous forest cover that could be observed as a function of polarization. As shown in Figure 5.2, there is very little difference between deciduous and coniferous forest on the HV image. On the HH image however, the deciduous forest cover has a distinct light tone whereas the coniferous forest cover has a relatively dark tone. Thus, deciduous and coniferous forest cover can be easily separated on the HH imagery due to the distinctive tonal differences, even though these cover types are very difficult to separate on the HV imagery.

Other features such as older clearcuts and fields having emergent vegetation tend to look very similar in both tone and texture on both polarizations. Although recent clearcuts are very dark in tone in both polarizations as compared to the surrounding forest cover, they are easier to separate from

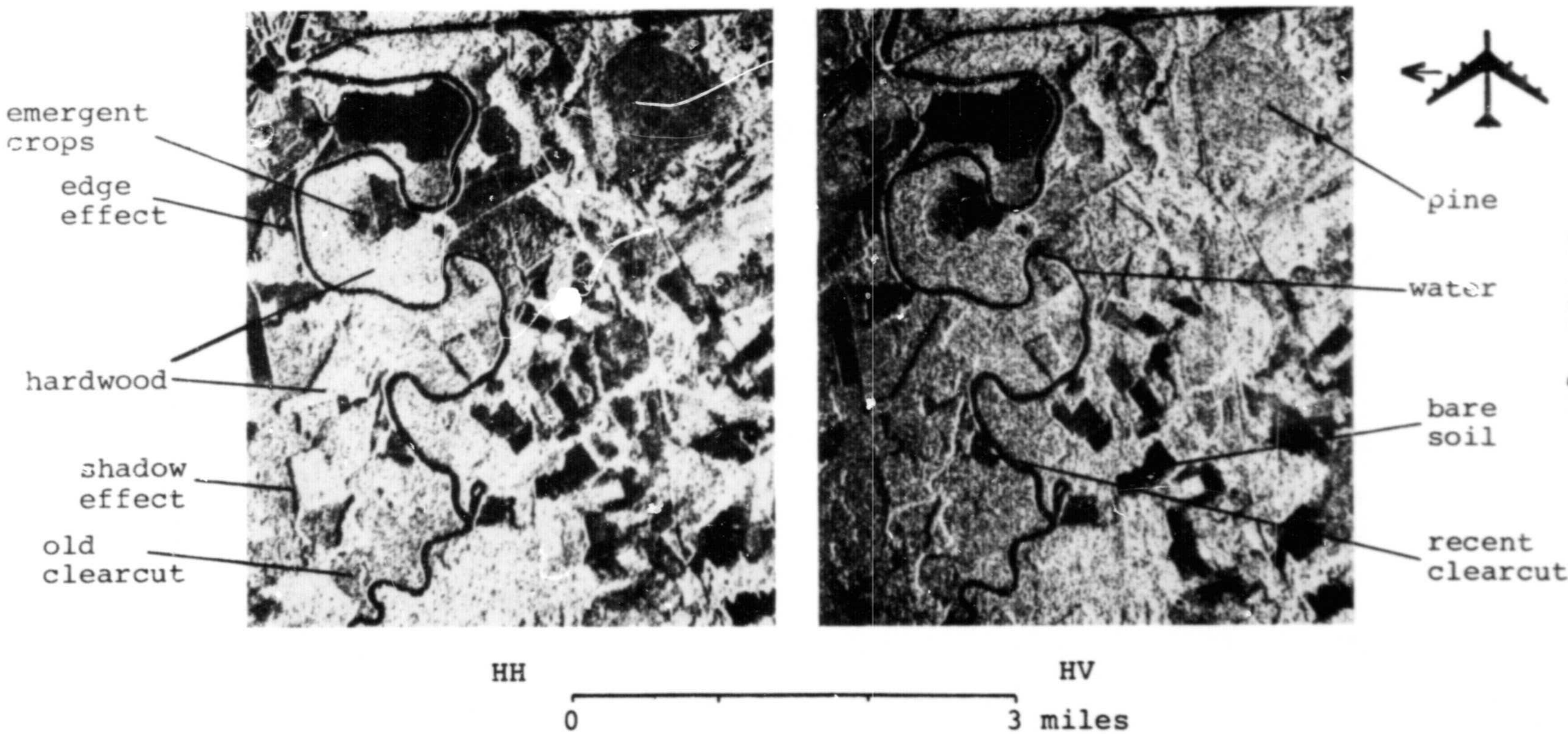

Figure 5.2. Enlargement of dual-polarized imagery showing tonal differences between deciduous and coniferous forest cover.

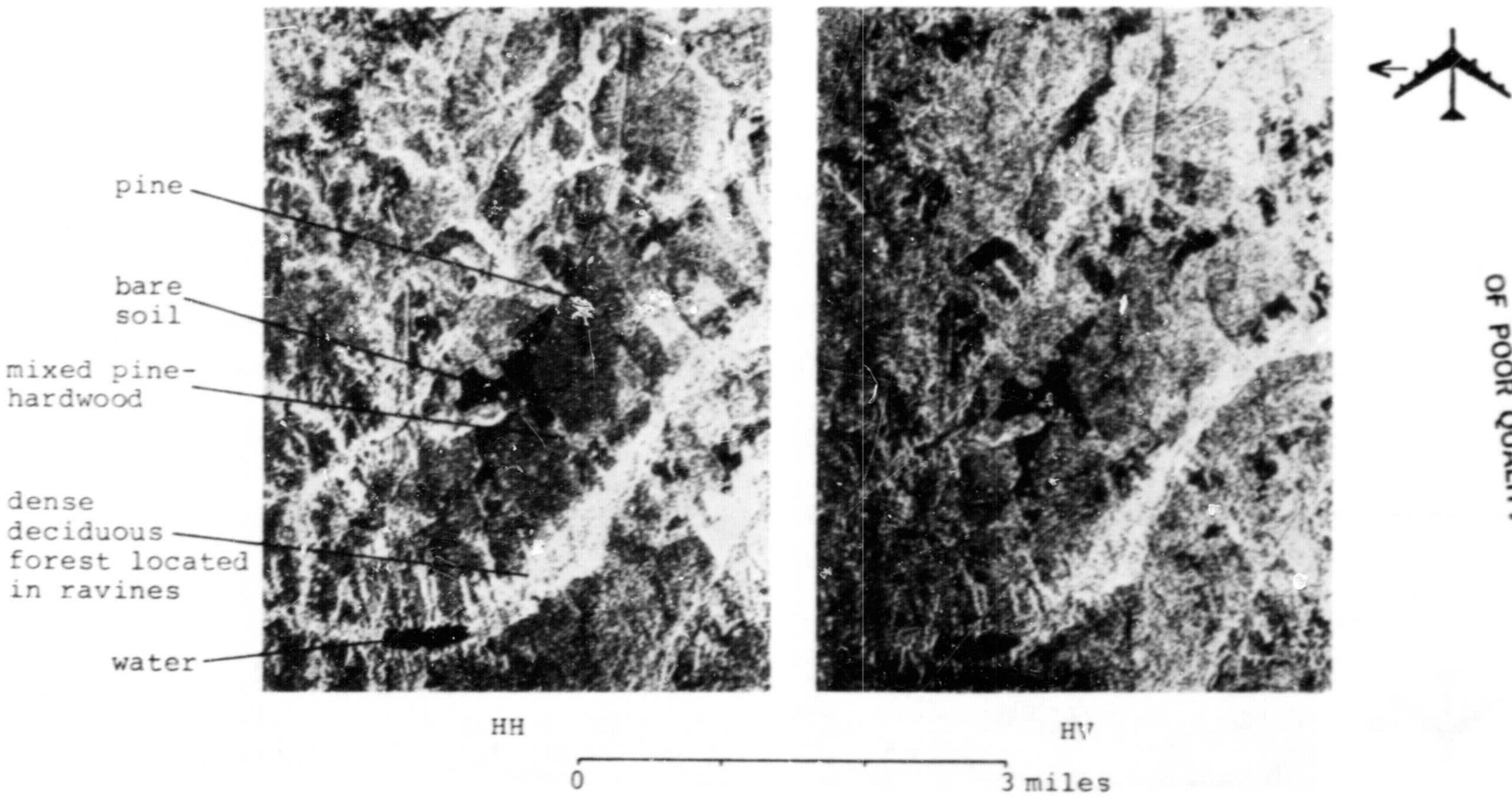

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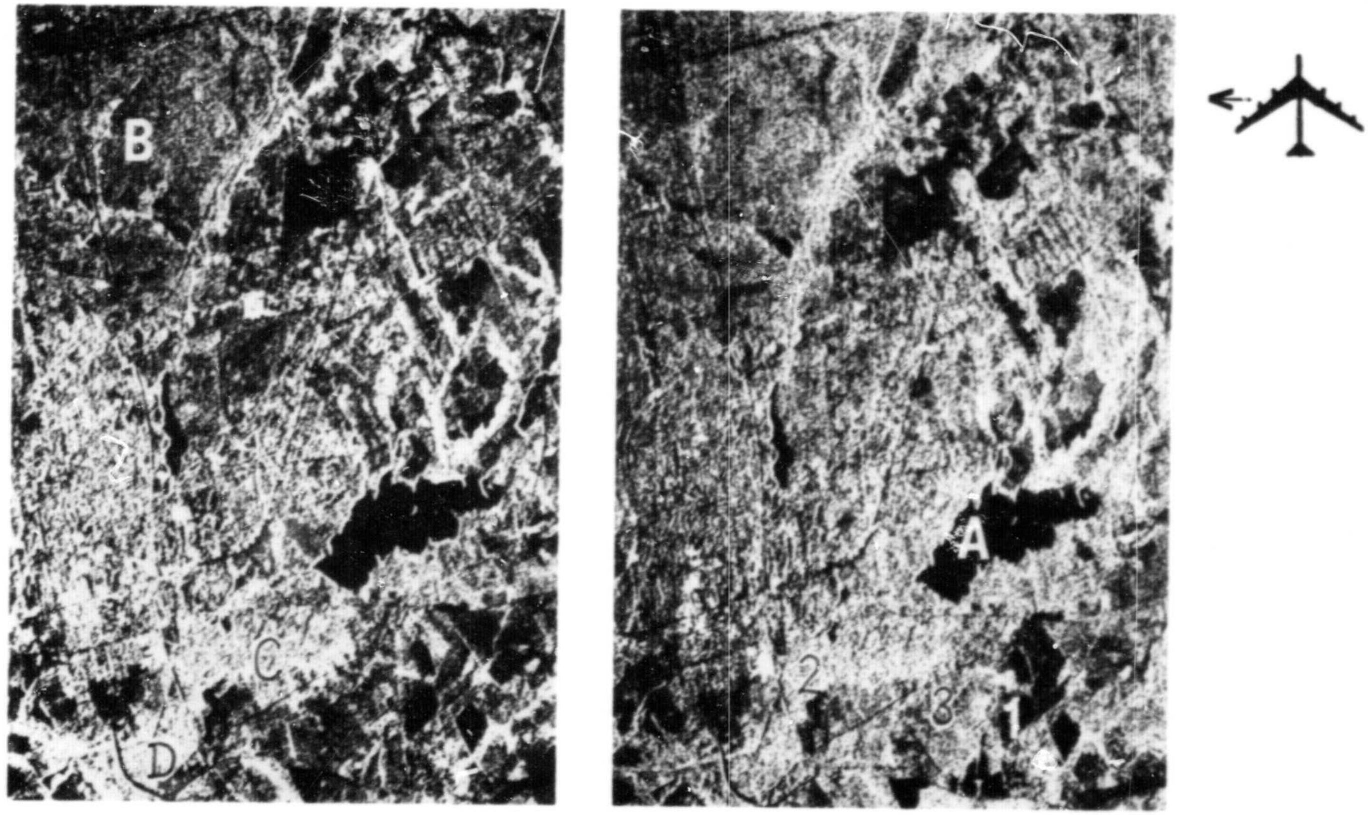
Figure 5.3. Example of radar imagery indicating distinct appearance of vegetated ravines on HH polarization.

coniferous and mixed cover types on the HV imagery. Water and smooth bare soil features have a distinctive black appearance on both polarizations due to the specular reflectance of the emitted radar signal away from the antenna. However, by using the shapes and speckling characteristics of some agricultural fields, water and fields with bare soil usually can be separated.

It should be noted that of the features identified on the color IR photography, several could not be identified on the SAR imagery. Old growth and second growth hardwood stands could not be separated. Water tupelo was very easy to identify on the color IR photography because of its distinctive color, but could not be identified at all on the SAR imagery. Table 5.2 summarizes the tonal and textural characteristics of the various forest and other cover types examined in this study. Examples of the tonal and textural characteristics are illustrated in Figure 5.4. A more detailed characterization of the appearance of the various cover types in each polarization is shown in Table 5.3. Table 5.3 is an expanded version of the summary in Table 5.2, and provides additional information concerning the variability in appearance of some of the cover types.

In summary, the qualitative analysis of the dual-polarized SAR imagery showed that certain forest cover features are more easily identified in one polarization than the other, while many non-forest features look very similar in both polarizations. Discriminating between coniferous stands and deciduous stands was easier on the HH image than on the HV image. However, this does not infer that the HH polarized image is better. The shadow and edge effect due to extreme differences in vegetation height help delineate the boundaries of clearcuts, and are much more prevalent on the HV image. Neither polarization is consistently better for identifying the various forest cover types examined.



HH HV

0 3 miles

Figure 5.4. Example of tonal and textural characteristics of SAR data (see Table 1).

Table 5.2. Tone and texture characteristics of various cover types in relation to polarization of the radar imagery.

	Tone[1/]		Texture[2/]	
Cover Type	HH	HV	HH	HV
Hardwood	white	light gray	grainy	grainy
Pine	dark gray	gray	speckled	speckled
Mixed Pine-Hardwood	dark gray	gray	grainy	speckled
Clearcut	dark gray	dark gray	grainy	grainy
Bottomland scrub	dark gray	dark gray	speckled	speckled
Pasture	dark gray	dark gray	grainy	grainy
Emergent Crops	dark gray	dark gray	grainy	grainy
Bare Soil	black	black	smooth	smooth
Water	black	black	smooth	smooth

[1/] Tone: (A) black; (B) dark gray; (C) light gray; (D) white

[2/] Texture: (1) smooth; (2) grainy; (3) speckled

(These letters or numbers indicate the examples of these descriptions shown in Figure 5.4)

The following points summarize the results obtained during the analysis:

1. Deciduous forest cover is easily identified on the HH image due to a distinctive light tone, whereas on the HV image these areas have a darker tone. (Figures 5.2 and 5.3)

2. Coniferous forest cover is dark in tone on the HH image and is somewhat lighter in tone on the HV image. (Figure 5.2)

3. Deciduous and coniferous forest cover are easily separated on the HH image due to their distinctive tonal differences, but are difficult to separate on the HV image. (Figure 5.2)

4. Dense deciduous forest stands located in ravines are easily identified on both polarizations because of the topographical pattern being highlighted by the response of the deciduous stands and partially highlighted by the slopes acting as angular reflectors. These patterns are more distinctive on the HH image than on the HV image. (Figure 5.3)

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Table 5.3. Descriptions of cover types identified on X-Band SAR imagery.

Cover Type	Tone		Texture	Comments
	HH	HV		
Hardwood	Very light in tone; light gray to white on imagery	Medium in tone; gray on near look side, light gray on far look side	Some speckle present on HH; slightly smooth to grainy. Increase in speckle on HV.	Shadow will appear to the west of stands and edge reflections will appear on the east side of stands, if non-forested land is adjacent. Most stands appear around drainage ways, water ways or on bottom land. Somewhat irregular in shape.
Regenerating Hardwood	Gray to light gray; some areas may appear almost white.	Gray throughout area	Grainy to speckled on both the HH and HV images	If forested land is adjacent to the clearcut areas, the east side will be in shadow while edge reflections will appear on west side. Usually irregular in shape and may have roads leading to stands. Blocks of trees may also be present within clearcut area.
Recent Clearcut	Dark in tone; dark gray on image	Varies in tone; dark gray (almost black) to light	Grainy; may have relatively large white patches within area.	Same as Regenerating Hardwood.
Pine	Dark gray; young stands and mature stands similar in tone.	Gray in tone; young stands appear to be darker in tone than mature stands.	Speckled; similar on both young and mature stands.	If non-forested land is adjacent to the clearcut areas, shadows will appear to the west of stands and edge reflections will appear on the east side of stands. Usually irregular in shape and may have roads leading to stands.
Pasture	Dark gray throughout field.	Dark gray to gray in tone.	Somewhat grainy on HH to a more speckled appearance on HV.	Somewhat regular in shape; if surrounded by forested land, the east side will be in shadow and edge reflections will appear on the west side. Individual trees may be present within the field.
Bare Soil	Black to dark gray in tone.	Black to dark gray in tone.	Fairly smooth to some graininess; depends on row direction or emergence of crops.	Regular in shape. If surrounded by forested land, edge reflections will appear on west side.
Crop	Light gray to white in tone.	Light gray to white in tone.	Smooth to grainy depending on the amount of crop cover present.	Same as Bare Soil.
Water	Black in tone.	Black in tone.	Smooth.	Irregular in shape (lakes) or very curvelinear (rivers). Edge reflection will appear on west border.
Urban	Light gray with some white splotches.	Gray with some white splotches.	Very speckled which decreases as one moves away from the center of urban area.	No definite boundary; many roads converging in the same general vicinity.

5. Older clearcuts and fields having emergent vegetation tend to look very similar in both tone and texture on both polarizations. (Figure 5.2)

6. Water and smooth bare soil features have a distinctive black appearance on both polarizations due to the specular reflectance of the emitted radar signal away from the antenna. (Figure 5.2)

7. Tupelo stands could not be distinguished from the surrounding hardwood forest on either the HH or HV imagery.

8. Differences in stand density and size class of forest stands could not be defined on either the HH or the HV polarization of the SAR data.

9. There is a distinctive banding effect on the HH image and a tonal variation related to range angle on the HV image which impact the ability of the interpretor to determine various cover types. These effects were also evident on other data sets of different flight lines. (Figure 5.3)

D. Classification Results

The next phase of the analysis involved computer classification of the SAR data. It was hoped that such a quantitative analysis might allow differentiation among cover types that could not be separated visually. Another objective was to determine if computer-aided analysis techniques that had originally been developed for MSS data could be effectively utilized with SAR data. In addition, the effectiveness of the SECHO classifier was to be evaluated for potential use with the SAR data, since this classifier utilizes both the "spectral" and spatial (e.g., radar speckle) information content in the data.

Due to the unique characteristics of the SAR data (as evidenced in part by the coherent speckle), a supervised classification was performed. In order to compare the SAR results with a classification of the TMS data, training and test fields were identified in both data sets throughout the area south of the city of Camden. On the 30 m data, this area consisted of 300 by 250 pixels, representing an area of 6 by 5 miles.

Both the training and test field locations were identified using the COMTAL Vision/20 (a digital image display device). To identify enough fields throughout the data set, each training and test field was limited in size to the "average" field size. The average field size was determined for each cover class by calculating the total area of each cover class and then determining the number of tracts of land that were represented by that cover class.

After identifying fields within each cover class, the fields were randomly divided into their training and test groups. The training fields were then divided into spectral classes within each cover class, if possible, based on the tonal variation within each cover class. Histograms were developed to determine if there were a sufficient number of training samples to accurately represent each spectral class. Statistics (i.e., mean vectors and covariance matrices) were calculated for each spectral class for use by the classification algorithms.

Since the SAR data had a distinct tonal variation across the flight line on the HV image (due to system characteristics), a statistical evaluation was performed to determine if the SAR training data should be separated into spectral classes based on the location of the individual fields across the flight line. To determine the significance of the tonal variation across the flight line, the flight line was first divided into six discrete strips. Fields of the dominant forest cover class, which was the hardwood class, were identified within each strip and their means and standard deviations calculated. Figure 5.5 illustrates the means and standard deviations for each strip for both the HH and HV channels. From this figure it is shown that the means are fairly uniform across the strips on the HH polarization. However, the means of the individual strips are increasing across the flight line on the HV polarization, thus graphically illustrating the tonal variation previously observed in the cross-track direction on the HV imagery.

An analysis of variance was performed on the data to determine the significance of the tonal variation. The means of the strips for the HH image were found not to be significantly different at $\alpha = 0.05$. However, the strip means of the HV image were found to be significantly different. Therefore, based on the Duncan's Multiple Range test, those fields which had column coordinates less than 240 on the 15 m SAR data and 120 on the 30 m SAR data were grouped into one set of "spectral" classes and those fields whose coordinates were greater were grouped into a second set of "spectral" classes. Table 5.4 shows, quantitatively, the differences in means and variances for the various cover types due to these look angle effects. Table 5.5 lists the number of "spectral" classes associated with each cover class (combined for

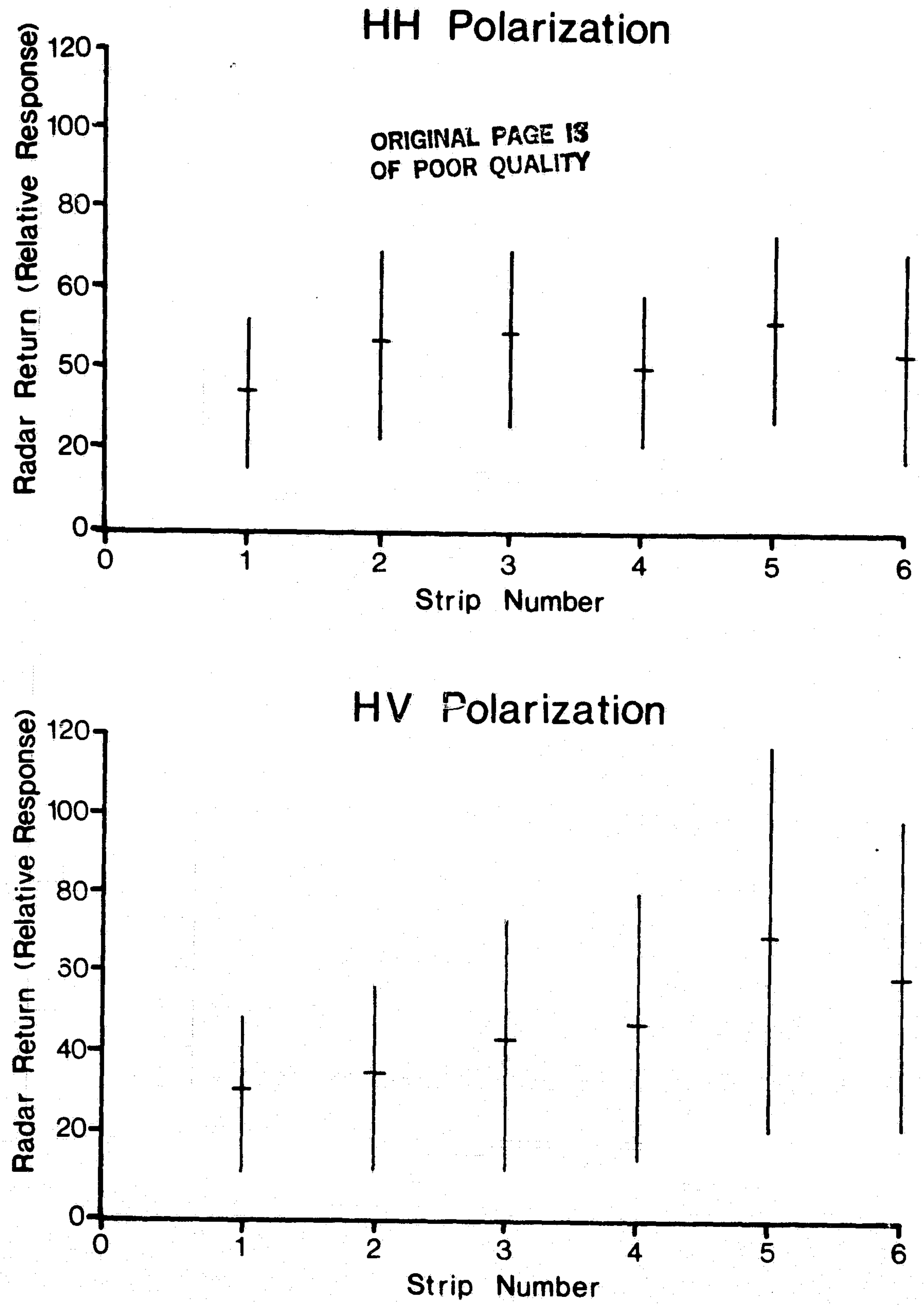

Figure 5.5. Plotted means and standard deviations for each strip for both the HH and HV polarizations using the 15 m SAR data set.

Table 5.4. Means and Standard Deviations for each cover class for both the left and right portions (i.e., spectral classes) of the 1980 SAR data sets.

		15 m				30 m			
		HH		HV		HH		HV	
Cover Class		Left	Right	Left	Right	Left	Right	Left	Right
SOIL	$\bar{X}$	6.4	13.8	6.8	16.6	6.7	13.4	6.7	17.0
	S	2.7	6.2	3.3	10.7	1.9	4.4	1.7	8.7
CROP	$\bar{X}$	22.1	14.6	26.9	18.1	21.9	15.4	26.3	19.0
	S	11.4	8.4	17.3	14.4	7.6	6.6	12.3	11.1
HDWD	$\bar{X}$	42.4	40.7	44.0	52.5	43.4	41.1	44.0	53.2
	S	21.7	21.6	32.6	38.1	15.0	14.1	21.5	25.1
RGHD	$\bar{X}$	33.4	34.9	37.2	56.3	33.4	34.4	36.9	56.3
	S	16.6	16.6	22.9	33.2	11.0	11.0	14.5	19.5
PINE	$\bar{X}$	10.4	14.4	19.4	39.1	10.8	14.6	20.0	39.2
	S	5.3	6.9	11.8	23.1	4.2	4.7	8.2	14.1
PAST*	$\bar{X}$		13.4		42.2		14.0		43.1
	S		6.8		24.6		5.5		16.7
WATR	$\bar{X}$	3.8	4.3	6.2	6.9	4.6	5.0	6.4	7.5
	S	1.3	2.0	3.8	2.4	2.6	3.0	3.0	1.9

*The pasture class only had representative fields on the right portion of the flight swath.

Table 5.5. The number of spectral classes, training pixels, and test pixels associated with each cover class for the quantitative analysis of the 1980 SAR data.

	No. of Spectral Classes			No. of Training Pixels			No. of Test Pixels		
Cover Class	SAR 15	SAR 30	MSS 30	SAR 15	SAR 30	MSS 30	SAR 15	SAR 30	MSS 30
PINE	2	2	3	845	251	120	840	249	134
HDWD	2	2	1	3332	935	824	3131	840	1495
RGHD	2	2	1	3027	849	929	1490	442	577
PAST	1	1	2	714	218	396	1239	360	271
CROP	2	2	3	2001	594	723	2250	690	575
SOIL	2	2	2	1704	466	196	1398	414	291
WATR	2	2	3	547	166	190	552	161	193
TOTAL	13	13	15	12170	3479	3378	10900	3156	3536

both sides of the flight line), and the numbers of pixels involved in the training and test data of both the SAR and MSS data sets.

The classification of the SAR data was, of course, limited to the two channels of data available (i.e., the two polarizations). Three different classification algorithms were tested — the GML (Gaussian Maximum Likelihood) classifier, the Per-Field classifier, and the SECHO (Supervised Extraction and Classification of Homogeneous Objects) classifier. The latter two are both contextual classifiers, in that they base the classification decision on both the mean and the variance of the spectral response over an area (a training or test field defined by the analyst in the case of the Per-Field classifier, or the "Homogeneous Object" defined by the algorithm in the SECHO classifier). In addition, both the 15 m and the 30 m SAR data sets were classified in order to evaluate the effect of spatial resolution on the SAR data. The 30 m SAR results were then compared to 30 m TMS data results in order to evaluate the effectiveness of the SAR data as compared to the TMS data.

The SAR 15 m data was classified using each of the three classification algorithms, and the results are given in Table 5.6 below. Figure 5.6 graphically depicts the overall classification results for the three classifiers. The overall differences between the three classifiers were significantly different, and, as shown in Figure 5.6, the classifiers that use spatial as well as spectral information (i.e., the PER-FIELD and SECHO classifiers), increased the overall classification performance by a factor of almost two as compared to the GML per-point classifier. However, the overall performance for all three classifiers was rather low. On a class by class basis, the results are rather mixed. Hardwood, regenerating hardwood (previously clearcut areas), crop and soil have much higher performances for both the PER-FIELD and SECHO classifiers than were obtained using the GML

Table 5.6. Test field classification results for the SAR 15 m data.[1/]

Cover Class	Classifier GML	PER-FIELD	SECHO
Pine	45.7[b]	37.4[a]	52.9[c]
Hardwood	37.2[a]	93.6[b]	99.4[c]
Regen. Hdwd.	28.3[a]	70.1[c]	57.9[b]
Pasture	25.1[b]	48.8[c]	16.0[a]
Crop	19.9[a]	35.3[b]	33.4[b]
Soil	50.1[a]	93.6[b]	94.1[b]
Water	83.9[b]	82.6[b]	58.0[a]
Overall	35.7[a]	68.4[c]	64.3[b]

[1/]Different superscripts indicate significantly different classification performances between the classifiers, based on a Newman-Keuls comparison with $\alpha = 0.10$.

classifier. However, although the performance for hardwood and soil was very high for both of the contextual classifiers, the performances for crop and pasture were low. The other cover types had mixed performances between the classifiers, and their performances were generally very low. For pine and pasture, the poor performances were attributed to the fact they had very similar radar returns and the classification algorithms could not discriminate between these two classes.[1/] This similarity can be seen in Figure 5.7, which shows the mean ± one standard deviation of the radar return for each of

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[1/]Appendix D contains performance tables showing commission and omission errors between cover types for all data sets and classifier combinations discussed in Section V of this report.

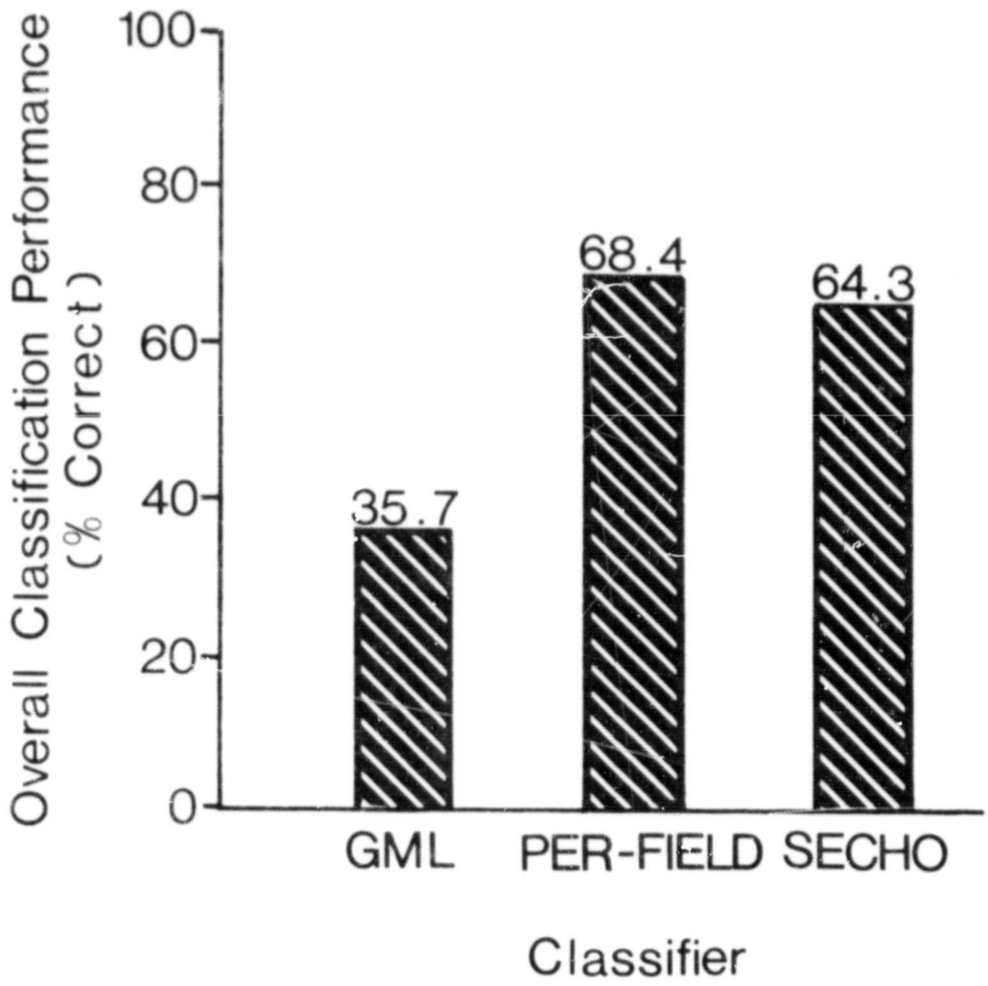

Figure 5.6. Overall test field classification performances for three classifiers using the 15 m SAR data.

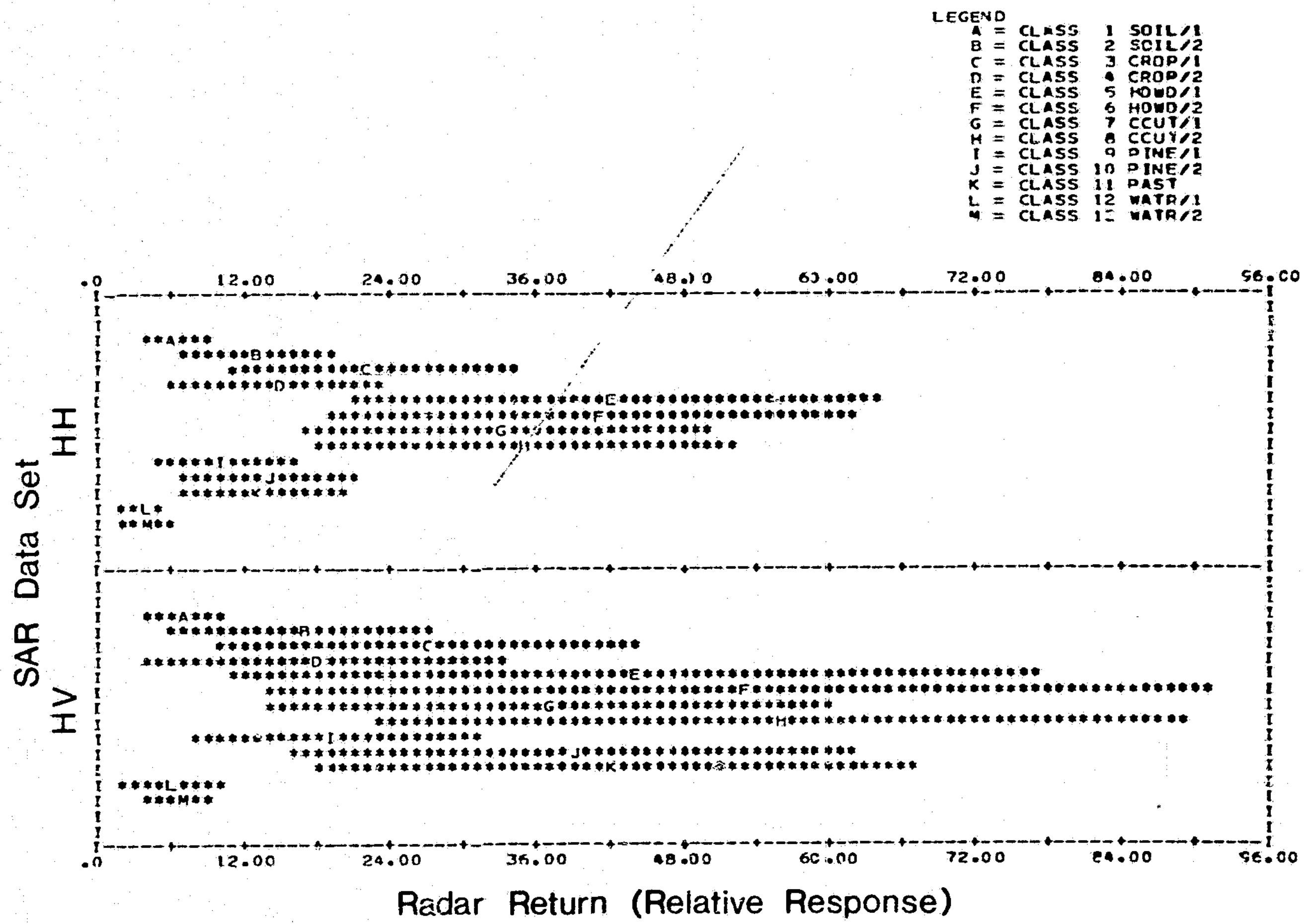

Figure 5.7. Coincident spectral plot (means plus and minus one standard deviation) for all cover type "spectral" classes for the 15 m SAR data.

"spectral" training classes defined. Many "spectral" classes within a single cover type, as well as different cover types clearly had very similar radar returns in both polarizations.

The water class had fairly high classification performances for both the GML and PER-FIELD classifiers, but a much lower performance for the SECHO classifier. This poor performance by the SECHO classifier was due to the algorithm, and more specifically, the "moving window" portion of the classification process. Since the majority of the water class was comprised of the Wateree River and the river is approximately 70 m in width, then the width of the river was represented by only six pixels for the SAR 15 m data set. The moving window was three pixels wide and thus, many times included boundary pixels. The resulting radar return recorded within the 3 pixel x 3 pixel window could be similar to that of other classes, resulting in misclassifications.

After the 15 m SAR data had been classified, the same three algorithms were used with the 30 m SAR data. Approximately the same areas in both data sets were used for training and test fields. The test field performances of the SAR 30 m data for the three classifiers are shown in Table 5.7 and in Figure 5.8. These results show that both the SECHO and PER-FIELD classifiers performed significantly better than the GML classifier. All three overall classification performances were found to be significantly different from each other. As seen in Table 5.5, the hardwood cover class had a very high performance for both the PER-FIELD and SECHO classifiers, and the hardwood, regenerating hardwood, pasture, and crop classes all had much higher classification accuracies for both the PER-FIELD and SECHO classifiers than the GML classifier. However, the pine cover class had a very low classification performance for the SECHO classifier. This was attributed to the large number

Table 5.7. Test field classification results for the SAR 30 m data.[1/]

Cover Class	Classifier		
	GML	PER-FIELD	SECHO
Pine	65.5[b]	90.4[c]	53.8[a]
Hardwood	52.6[a]	93.3[b]	97.9[c]
Regen. Hdwd.	45.0[a]	66.1[b]	63.6[b]
Pasture	19.7[a]	41.9[b]	43.6[b]
Crop	85.8[a]	34.6[b]	50.9[c]
Soil	71.0[b]	46.4[a]	65.0[b]
Water	62.7[b]	70.8[b]	39.8[a]
Overall	45.9[a]	63.3[b]	65.8[c]

[1/] Different superscripts indicate significantly different classification performances between the classifiers, based on a Newman-Keuls comparison with $\alpha = 0.10$.

of pine test pixels that were classified as pasture (see Appendix D). All three classifiers performed poorly in discriminating pasture and pine from each other, with the GML classifier having a particularly low accuracy for pasture. Because the radar returns for the soil and water classes were very similar (as shown in Figure 5.9), there was considerable confusion between these two classes. The low PCC performance for the water class using the SECHO classifier was again due to the "window size" utilized in the SECHO classifier, as well as the spatial resolution of the pixels. In comparing Figures 5.9 and 5.7, it is clear that the degradation of the spatial resolution to 30 meters caused a distinct decrease in the variance of the radar returns for most of the "spectral" classes involved in these classifications, which should cause a higher classification performance for the 30 m data when using the GML algorithm.

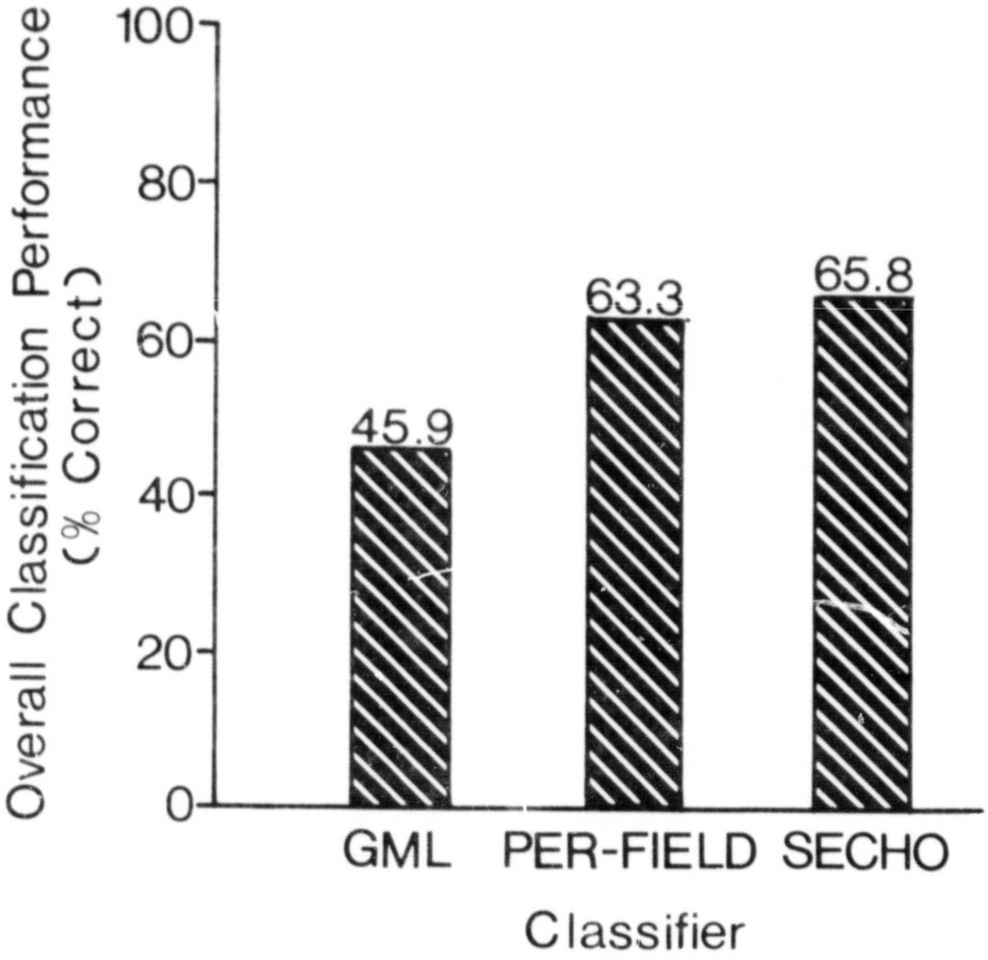

Figure 5.8. Overall test field classification performances for three classifiers using the 30 m SAR data.

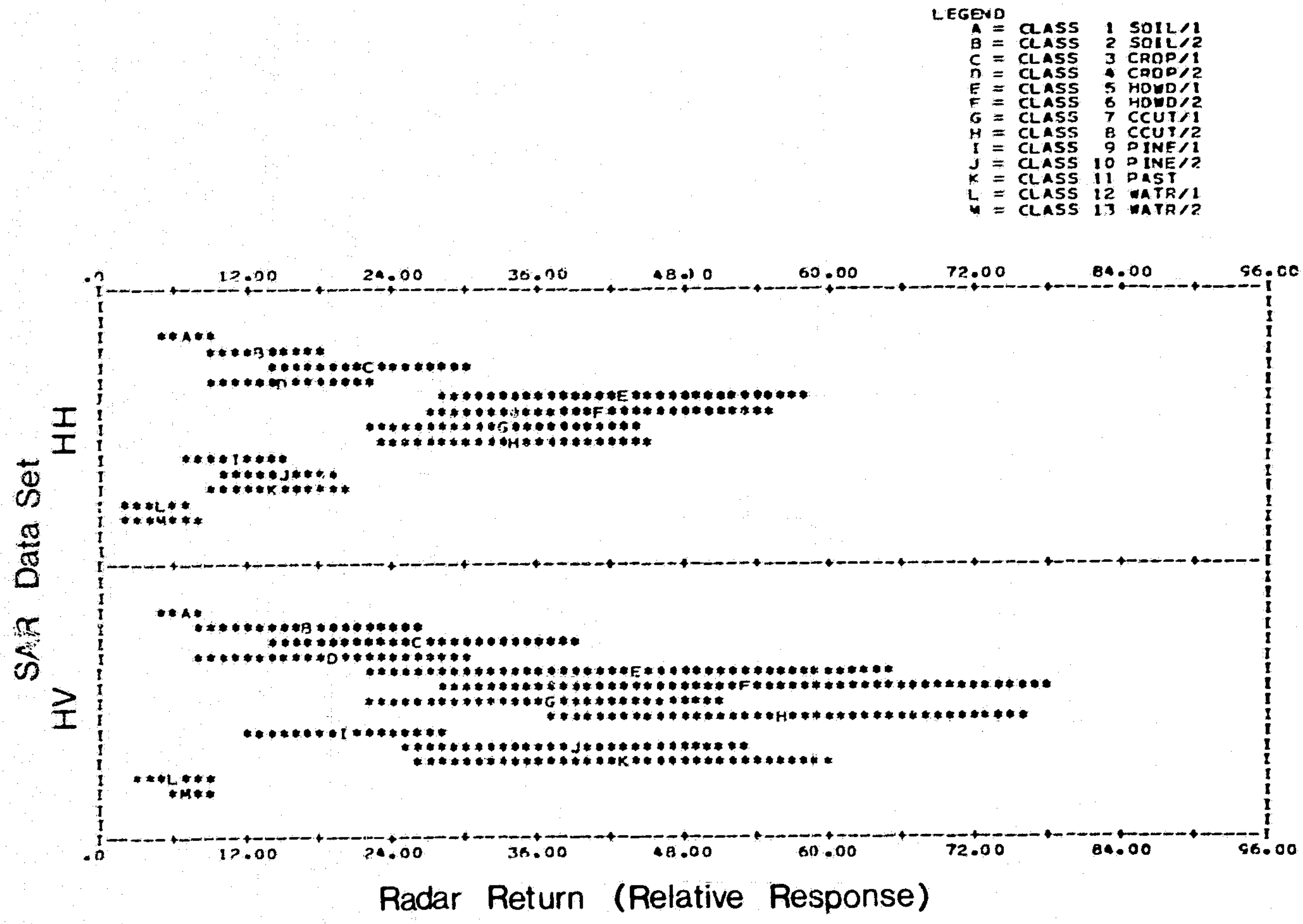

Figure 5.9. Coincident spectral plot (means plus and minus one standard deviation) for all cover type "spectral" classes for the 30 m SAR data.

The overall PCC performances for the 15 m SAR and 30 m SAR data using the three classifiers are compared in Figure 5.10. The results of the statistical evaluation between the data sets are given in Table 5.8. The overall classification performances between the two data sets were found to be significantly different for the GML and PER-FIELD classifiers, but they were not significantly different for the SECHO classifier.

For the GML classifier, these results show that overall performance tends to increase by degrading the spatial resolution, as anticipated. This is because the spectral variability associated with each cover class is reduced in the 30 m data, and the amount of overlap between the "spectral" distributions is therefore reduced, thus reducing the probability of misclassification.

The comparison of the two data sets for the PER-FIELD and SECHO classifiers show that the overall results are rather similar, with the performance of the 15 m SAR data set being slightly higher than the 30 m SAR data set when using the PER-FIELD classifier. These results would tend to indicate that by

Table 5.8. Statistical comparison between the overall classifications of the 15 m and 30 m SAR data sets, for each classification algorithm.[1/]

	Data Set	
Classifier	SAR 15 m	SAR 30 m
GML	35.7[a]	45.9[b]
PER-FIELD	68.4[b]	63.3[a]
SECHO	64.3[a]	65.8[a]

[1/]Different superscripts indicate significantly different classification performances between the data sets, based on a Newman-Keuls comparison with $\alpha = 0.10$.

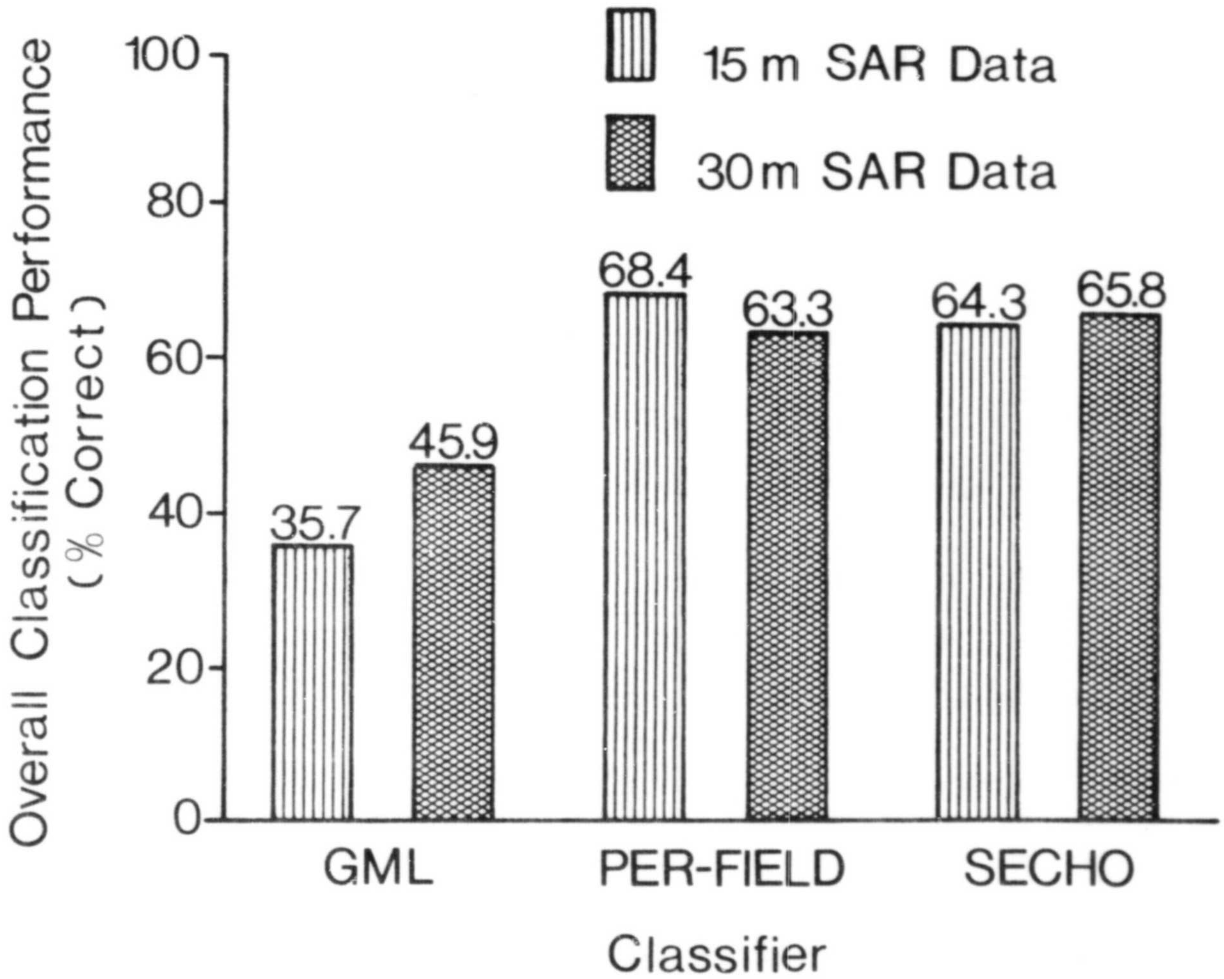

Figure 5.10. The overall classification performances for three classifiers using the 15 m and 30 m SAR data.

degrading the spatial resolution, overall classification performances may not increase when using contextual classifiers. However, because both contextual classifiers performed much better than the GML classifier with either spatial resolution data set, it would suggest that algorithms that incorporate both spectral and spatial information in the classification decision will produce significantly increased classification performances when using SAR data.

The classification performances by cover class for the three classifiers examined and for both the 15 m and SAR 30 m data sets are shown in Figure 5.11. The hardwood (HDWD) class has a high classification performance for both data sets using both the PER-FIELD and SECHO classifiers. Also, the crop and regenerating hardwood (RGHD) cover classes had higher performances using either of the textural classifiers than when the GML classifier was used. Such results would be expected, since hardwood, regenerating hardwood, and crop cover classes all had relatively large "spectral" variances in the SAR data (as shown in Figure 5.7 and 5.9), and both the PER-FIELD and SECHO classifiers can incorporate this information along with the spectral information to better separate the "spectral" distributions. However, the classification performances of the regenerating hardwood and crop classes were relatively low for all three classifiers due to misclassification with other vegetation classes having similar "spectral" distributions.

The cover classes pine, pasture, soil, and water had irregular patterns of classification performances. As previously mentioned, pine and pasture had similar levels and distributions of radar return, in spite of the significant physical differences between these two cover types. The similar radar data values caused considerable confusion and misclassification between these two cover types for all three classifiers.

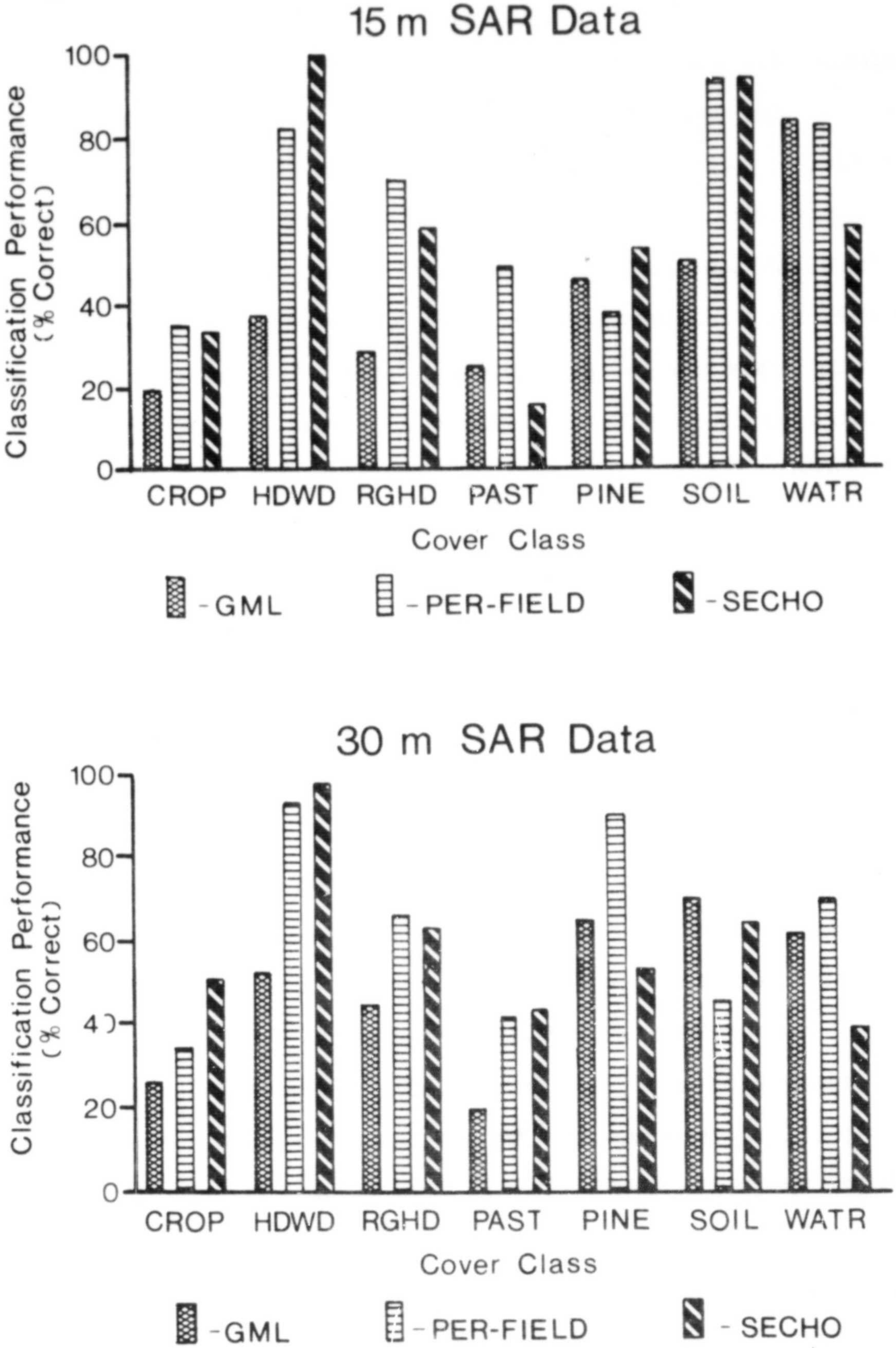

Figure 5.11. Classification performances by cover class for the three classifiers, and for both the 15 m and 30 m SAR data sets.

For the 30 m data, soil had a somewhat higher classification performance with the GML classifier than with either contextual classifier. However, when using the 15 m data, soil had a much higher classification performance for the PER-FIELD and SECHO classifiers than the GML classifier. The pixel-to-pixel variation in the 15 m data set was apparently very useful in helping the contextual classifiers to identify bare soil correctly. By degrading the resolution, the amount of pixel-to-pixel variation was reduced within each 30 m pixel in the fields of bare soil.

The 30 m TMS data covered approximately the same area as both the 15 m and 30 m SAR data sets. The training and test fields were generated using procedures that were similar to those used for the SAR data and representing the same cover types. However, in some cases, the field locations for a particular cover type were not the same between the SAR and TMS data sets due to changes in the cover type (e.g., bare soil to crops) as a result of differences in data collection dates (i.e., SAR = June 30 versus TMS = August 29, 1980). Eight channels were available for classification; however, only the best three channel combination was used in the classification. Channels 3, 5, and 8 (0.63-0.69 μm, 1.00-1.30 μm, and 10.4-12.8 μm, respectively) were identified as the best three channel combination using divergence as the separability measure between all possible combinations for the given spectral classes.

The overall and cover type classification performances for the three classifiers using the 30 m TMS data is given in Table 5.9. For all three classifiers, the overall classification performances were greater than 90 percent and were found to be significantly different. These results indicate that for a limited area and for the given cover classes, a reasonable classification of the test could be performed using only three channels of TMS data.

Table 5.9. Overall and cover class classification test performances for each classifier, using the 1980 30 m TMS data (supervised training statistics).[1/]

	Classifier		
Cover Class	GML	PER-FIELD	SECHO
Pine	75.4[a]	73.9[a]	75.4[a]
Hardwood	91.2[a]	100.0[c]	96.9[b]
Regen. Hdwd.	86.7[a]	89.6[a]	89.1[a]
Pasture	87.1[a]	94.1[b]	91.5[ab]
Crop	95.3[a]	100.0[b]	95.1[a]
Soil	99.3[a]	100.0[b]	97.6[a]
Water	94.8[a]	93.8[a]	99.5[b]
Overall	91.1%[a]	96.5%[c]	94.3%[b]

[1/]Different superscripts indicate significantly different classification performances between the classifiers, based on a Newman-Keuls comparison with $\alpha = 0.10$.

In addition, the overall classification performances for both the PER-FIELD and SECHO algorithms were significantly higher than the GML performance. This again emphasizes the point that by using additional information (i.e., texture), classification performances can be improved.

The overall classification performances for the 15 m SAR, 30 m SAR, and 30 m TMS data sets using the three classifiers are given in Figure 5.12. The statistical comparisons, by cover type and for the overall classification performances are given in Table 5.10. For all classifiers, the 30 m TMS data set performed significantly better than either the 15 m or 30 m SAR data sets. This was found both for the individual cover types and for the overall classification comparisons. However, in evaluating these results comparing SAR and TMS data, one must keep in mind that the classification of the SAR data

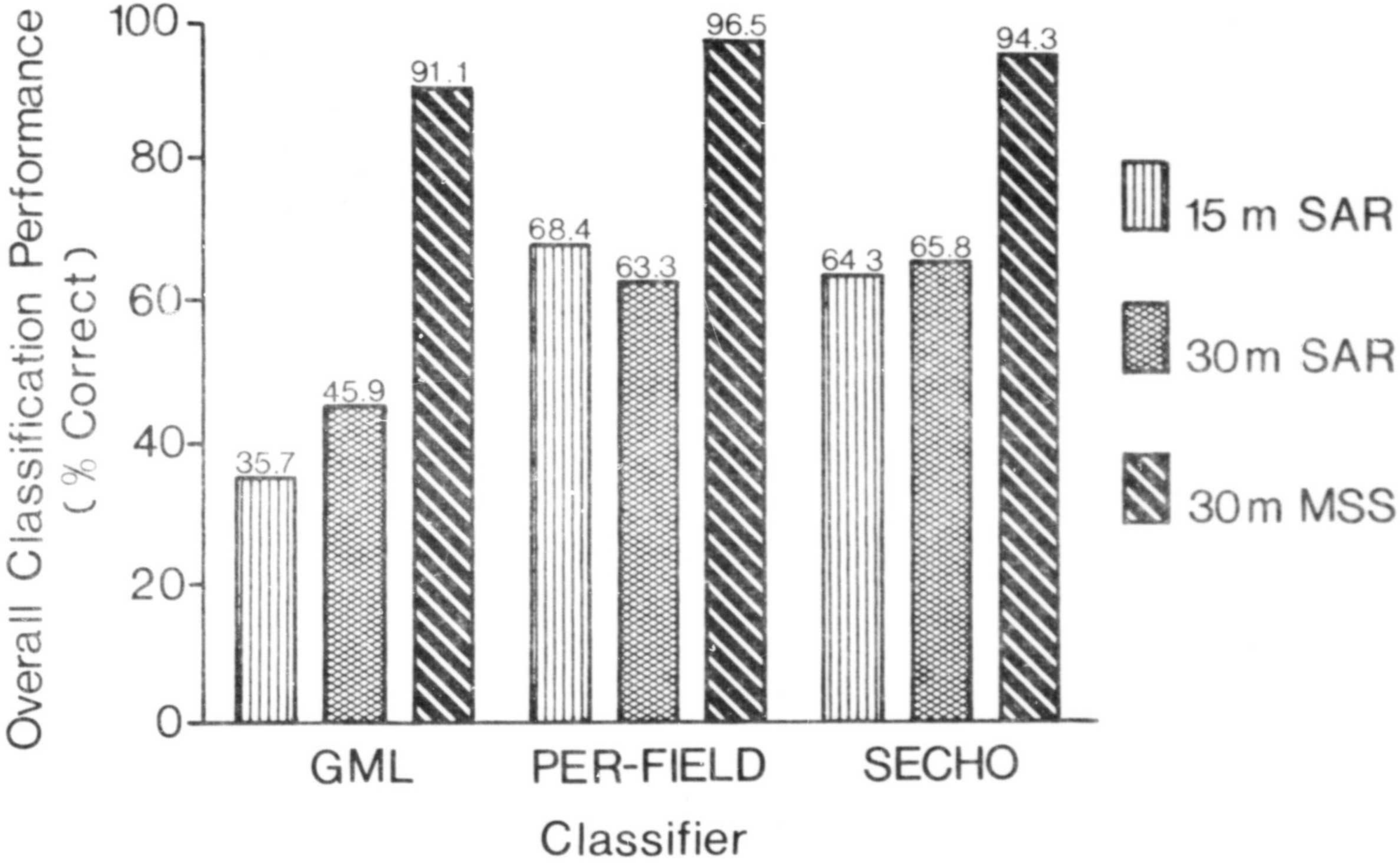

Figure 5.12. Overall test classification performance for the 15 m SAR, 30 m SAR, and 30 m TMS data for the three classifiers.

Table 5.10. Classification test field performances for the 15 m and 30 m SAR data and the 30 m TMS data for each cover type by classifier.[1/]

	GML			PER-FIELD			SECHO		
Cover Type	SAR 15	SAR 30	MSS 30	SAR 15	SAR 30	MSS 30	SAR 15	SAR 30	MSS 30
PINE	45.7[a]	[illegible].5[b]	75.4[b]	37.4[a]	90.4[c]	73.9[b]	52.9[a]	53.8[a]	75.4[b]
HDWD	37.2[a]	52.6[b]	91.2[c]	93.6[a]	93.3[a]	100.0[b]	99.4[b]	97.9[a]	96.9[a]
RGHD	28.3[a]	45.0[b]	86.7[c]	70.1[a]	66.1[a]	89.6[b]	57.9[a]	63.6[a]	89.1[b]
PAST	25.1[a]	19.7[a]	87.1[b]	48.8[a]	41.9[a]	94.1[b]	16.0[a]	43.6[b]	91.5[c]
CROP	19.9[a]	25.8[b]	95.3[c]	35.3[a]	34.6[a]	100.0[b]	33.4[a]	50.9[b]	95.1[c]
SOIL	50.1[a]	71.0[b]	99.3[c]	93.6[b]	46.4[a]	100.0[c]	94.1[b]	65.0[a]	97.6[c]
WATR	83.9[b]	62.7[a]	94.8[c]	82.6[b]	70.8[a]	93.8[c]	58.0[b]	39.8[a]	99.5[c]
Overall	35.7[a]	45.9[b]	91.1[c]	68.4[b]	63.3[a]	96.5[c]	64.3[a]	65.8[a]	94.3[b]

[1/] Different superscripts indicate significant differences, based on the Newman-Keuls test with $\alpha = 0.10$. The statistical evaluation was conducted between data sets for each classifier, and not for all possible data set/classifier combinations.

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involved only two channels of data of a single wavelength. If SAR data from one or two additional wavelengths were available, it is conceivable that the SAR data could provide results as good as or better than those obtained with the TMS data.

The major results for the quantitative analysis of the SAR data can be summarized as follows:

1. The HH and HV polarized data sets had independent geometric distortions which required special preprocessing techniques to successfully digitally overlay the two sets of data.

2. Significant improvements in overall classification performances were achieved using both the PER-FIELD and SECHO classifiers versus the GML per-point classifier for both the SAR and TMS data sets.

3. Pine and hardwood cover classes could be reliably differentiated on the SAR (as well as the TMS) data.

4. Pine and pasture cover classes, and bare soil and water cover classes were consistently confused with each other on this X-band SAR data.

5. There were statistically significant differences in radar return across the flight-line due to look-angle effects for many cover types, particularly in the HV polarized data.

6. Degrading the spatial resolution of the SAR data (from 15 m to 30 m) caused the overall percent classification performance for the GML per-point classifier to increase due to the better separation of the probability density functions associated with some of the cover types. However, degrading the spatial resolution, had either no effect or a negative effect on the overall classification performance of the contextual classifiers (i.e., PER-FIELD or SECHO).

7. The various threshold parameters (i.e., window size, homogeneity, and annexation) used in the SECHO classifier are data dependent and are strongly influenced by the size, shape, and textural characteristics of the cover types being classified.

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VI. SUMMARY AND RECOMMENDATIONS

A. Summary

During the course of this investigation, the qualitative and quantitative analysis of both the Thematic Mapper Simulator (TMS) and the Synthetic Aperture Radar (SAR) data produced a number of results and conclusions, which can be summarized as follows:

Spatial Resolution Study

1. The use of successively higher spatial resolution data resulted in lower overall classification accuracies when classifications were conducted with a "per-point" GML classifier.

2. Higher classification accuracies were achieved with the "per-point" classifier when using 60 x 75 meter (as opposed to finer) spatial resolution data in cover classes associated with relatively high levels of spectral variability across adjacent pixels (i.e., old-age hardwood, second growth hardwood, pine forest, and clearcut areas).

3. Differences in classification accuracies achieved with data of different spatial resolutions were not significant ($\alpha = 0.10$) for cover classes associated with relatively low levels of spectral variability across adjacent pixels (i.e., pasture, crops, bare soil, or marsh vegetation).

Waveband Evaluation Study

1. Use of four wavelength bands produced considerably better classification results than when only two or three wavelength bands were utilized.

2. Maximum overall classification performances were obtained when all wavelength bands were utilized.

3. The increase in overall classification performance when more than four wavelength bands were utilized was minimal, therefore indicating that an appropriate set of four wavelength bands provides the best combination of relatively high classification accuracy and minimal computer time.

4. Classifications using the 1979 data set and various three and four wavelength band combinations indicated the importance of both the visible and near-infrared portions of the spectrum for accurately classifying various forest and other cover types.

5. These results, which were primarily focused on differentiation of various types of healthy vegetative cover, did not indicate any

particular advantage for using wavelength bands in portions of the spectrum beyond those to which Silicon detectors (used in Multi-Linear Array systems) are sensitive.

6. The Supervised method of developing training statistics provided slightly better overall classification results than the Multi-Cluster Blocks technique for both the 1979 and 1980 data sets. It would appear that for situations where accurate, reliable reference data (i.e., "ground truth") is available over the entire study area and for data having fine spatial resolution, the Supervised technique is generally best. It is particularly useful for waveband evaluation studies involving different cover types.

7. Overall classification accuracies based on the "best 3" wavebands defined by the <u>average</u> transformed divergence values were significantly higher than those based on the "best 3" wavebands defined by the <u>minimum</u> transformed divergence values.

<u>Comparison Among Classification Algorithms</u>

1. The SECHO algorithm consistently resulted in higher overall classification performances than were obtained with the GML algorithm, regardless of the data set or training statistics being utilized.

2. The L-2 Minimum Distance algorithm produced significantly less accurate classifications than were obtained using either the GML or the SECHO algorithms.

3. Overall classification performances of 85-90%, based on test data sets, were obtained for both the 1979 and 1980 TMS data when four or more wavelength bands were utilized in conjunction with the SECHO classifier and either the Supervised or Multi-Cluster Blocks training statistics.

4. Phenological effects caused distinct differences in spectral response for some cover types, especially tupelo, when comparing the 1979 and 1980 data.

<u>Principal Components or Karhunen-Loeve (K-L) Transformation of the TMS Data</u>

1. The K-L transformation (with 4 components) significantly decreased the overall classification performance for both the GML and SECHO classifiers, but the overall classification for the L-2 classifier was generally increased.

2. For individual cover types, the GML and SECHO performances tended to be rather similar (both would either increase or decrease by a similar amount for a particular cover class with a K-L transformation) but the L2 classifier tended to react in the opposite way; i.e., when the GML and SECHO classification cover class performances decreased with a K-L transformation, the L2 increased, and vice-versa (with the exception of the CCUT and WATER categories).

3. A K-L transformation and the L-2 classifier improved all cover class performances when using only three channels (i.e., components) and most cover class performances when using four channels.

4. A K-L transformation and the GML classifier improved some (i.e., half) of the classification performances for the individual cover classes when using three channels (components), but when using four channels the classification performances were often considerably better with untransformed data.

5. In general, it appears that for classifications using fewer number of channels (features) than is optimum for a particular data set (i.e., the intrinsic dimensionality of the data, which in this case is four), a K-L transformation will improve overall and most cover class performances. However, if the number of channels used is equal to the intrinsic dimensionality of the data, the original untransformed data appears to provide better class separability and subsequent classification performance.

Qualitative Analysis of the SAR Data:

1. Deciduous forest cover is easily identified on the HH image due to a distinctive light tone, whereas on the HV image deciduous forest cover has a darker tone.

2. Coniferous forest cover is rather dark in tone on both the HH and HV polarization imagery. Therefore, deciduous and coniferous forest cover are easily separated on the HH image due to their distinctive tonal differences, but are difficult to separate on the HV image.

3. Dense deciduous forest stands located in ravines are easily identified on both polarizations because the topographical pattern is highlighted by the response of the deciduous forest cover and also highlighted by the slopes which serve as angular reflectors. These patterns are more distinctive on the HH image than on the HV image.

4. Regenerating hardwood stands and fields having emergent vegetation tend to look very similar in both tone and texture on both polarizations.

5. Pine stands and pastures are both rather dark in tone in both the HH and HV polarizations and are therefore very difficult to differentiate on this X-band SAR data, in spite of the distinct differences in the physical characteristics of these cover types.

6. Water and smooth bare soil features have a distinctive black appearance on both polarizations due to the specular reflectance of the emitted radar signal away from the antenna.

7. Tupelo stands could not be distinguished from the surrounding hardwood forest on either the HH or HV imagery.

8. Differences in stand density and size class of forest stands could not be defined on either the HH or the HV polarization of the SAR data.

9. In the data set used in this study, there was a tonal variation related to range angle on the HV image and a distinctive banding effect on the HH image which impacted the ability of the interpreter to reliably identify various cover types throughout the entire data set. These effects were also evident on data sets for other flight lines.

Quantitative Analysis of the SAR Data:

1. The HH and HV polarized data sets had independent geometric distortions which required special preprocessing techniques to successfully digitally overlay the two sets of data.

2. There were statistically significant differences in radar return across the flight-line due to look-angle effects for many cover types, particularly in the HV polarized data.

3. Since only one wavelength (X-Band), represented by two channels (HH and HV polarizations) of SAR data were available for analysis, overall classification performances of only about 65% were obtained with the SAR data. It is believed that additional wavelengths of SAR data would enable significantly higher classification performances to be achieved.

4. Significant improvements in overall classification performances were achieved using both the PER-FIELD and SECHO contextual classifiers versus the GML per-point classifier for both the SAR and TMS data sets.

5. Pine and hardwood cover classes could be reliably differentiated on both the SAR and TMS data.

6. Pine and pasture cover classes, and bare soil and water cover classes were consistently confused with each other on this X-band SAR data.

7. Degrading the spatial resolution of the SAR data (from 15 m to 30 m) caused the overall percent classification performance for the GML per-point classifier to increase due to the better separation of the probability density functions associated with some of the cover types. However, degrading the spatial resolution had either no effect or a negative effect on the overall classification performance of the contextual classifiers (i.e., PER-FIELD or SECHO).

8. The various threshold parameters (i.e., window size, homogeneity, and annexation) used in the SECHO classifier are data dependent and are strongly influenced by the size, shape, and textural characteristics of the cover types being classified.

In conclusion, although Thematic Mapper data will undoubtedly be better than the current Landsat data from a mensurational standpoint, these preliminary results — which showed a decreased classification performance with higher (e.g., smaller) spatial resolution — tend to indicate that conventional per-point classification techniques may not be effective when using higher resolution data, particularly for areas involving classification of forest cover. Thus, classification techniques such as SECHO (which utilizes the spatial variability in addition to the mean spectral response of an entire forest stand or agricultural field), need to be further tested and refined for use with Thematic Mapper data.

The results of this investigation indicated that the Supervised technique for developing training statistics and the Sample Block Test Data approach for defining a statistically valid set of test data were effective, and that the average Transformed Divergence — based on the "best" four wavelength bands — defined by the Feature Selection processor in LARSYS enabled an optimum sub-set of wavebands to be defined. Use of fewer than four wavelength bands resulted in significantly lower classification performances, while more than four wavelength bands did not cause significant improvements in overall classification accuracy. Likewise, a Principal Components transformation did not prove useful for increasing classification performance when either the SECHO or GML classification algorithm were utilized with four channels of data. Comparison among different classification algorithms indicated that the SECHO contextual classifier provided the best overall classification results.

The SAR data could be used to separate some cover types with a high degree of reliability, but other cover types could not be adequately separated, even though they were physically very different. The value of <u>multiple</u> frequencies (particularly the longer wavelengths) as well as multiple polarizations of SAR data must be assessed in order to develop a better understanding of the true capabilities and limitations of SAR data for mapping forest cover types and their characteristics. However, such studies should be conducted using digitally—rather than optically—processed SAR data.

B. Recommendations

1. Contextual classifiers (e.g., SECHO), must be more fully developed and evaluated in order to assess the importance of such classifiers for effectively analyzing higher spatial resolution data such as that obtained by the Thematic Mapper.

2. Additional evaluations of Principal Component Transformations should be conducted with Thematic Mapper data in order to better assess the potential advantages and limitations of such data processing techniques in operational situations.

3. An effective and legitimate methodology for combining errors of commission and errors of omission is needed in order to provide a more meaningful measure of overall classification performance. In addition, a statistically valid but economically feasible methodology for defining test data sets (such as the "Sample Block Test Data" method developed in this study) needs to be tested and standardized for use by different researchers using computer-aided analysis techniques.

4. Digitally processed SAR data of multiple wavelengths and polarizations should be analyzed to better understand the capabilities and limitations of the microwave portion of the spectrum for mapping forest cover types and characteristics.

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APPENDICES A-D

APPENDIX A (Tables 1-36)

1979 Waveband Evaluation Classification Results and Statistical Analysis Tables

Table 1. Summary table of overall classification results, table location and channel subsets of the 1979 Waveband Evaluation: GML algorithm, sample block test data.

WAVEBAND COMBINATION	1 0.45- 0.52	2 0.52- 0.60	3 0.63- 0.69	4 0.76- 0.90	5 1.00- 1.30	6 1.55- 1.75	7 10.4- 12.5	GML Training Statistics Supervised	 MCB
"Best 2"		X			X			80.5% (Table 2)[1/]	81.5% (Table 15)
"Best 3"	X		X			X		78.4% (Table 3)	
	X		X		X				76.0% (Table 16)
"Best 4"		X		X	X		X	88.1% (Table 4)	
	X		X	X		X			86.1% (Table 17)
"Best 5"		X	X	X		X	X	88.3% (Table 5)	
	X	X	X	X		X			87.6% (Table 18)
"Best 6"	X	X		X	X	X	X	89.9% (Table 6)	
	X		X	X	X	X	X		87.4% (Table 19)
All 7	X	X	X	X	X	X	X	90.7% (Table 7)	88.7% (Table 20)
Visible	X	X	X					81.0% (Table 8)	72.2% (Table 21)
Reflective IR				X	X	X		71.9% (Table 9)	64.6% (Table 22)
"Best 3 minus Thermal IR"	X		X			X		78.4% (Table 3)	
	X		X		X				76.0% (Table 16)
"Best 3 minus Middle IR"			X	X	X			85.4% (Table 10)	
	X		X		X				76.0% (Table 16)
"Best 3 minus Near IR"	X		X			X		78.4% (Table 3)	
		X	X			X			82.1% (Table 23)
"Best 3 minus Reflective IR"	X	X	X					81.0% (Table 8)	
	X	X					X		64.3% (Table 24)
Simulated Landsat		X	X	X	X			88.9% (Table 12)	87.8% (Table 26)
Four channel subsets with one channel from each wavelength region			X		X	X	X	83.4% (Table 13)	85.3% (Table 27)
		X		X		X	X	87.0% (Table 14)	86.4% (Table 28)

[1/] Table numbers refer to the classification performance tables in Appendix A of this report.

Table 2. Waveband Evaluation Classification Results Using Channels 2 & 5 (the best 2). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	87.0	674	46	25	29	0	1	0	0
HARDWOOD	7269	85.9	588	6244	229	126	0	82	0	0
TUPELO	118	41.5	4	2	49	19	11	33	0	0
CLEARCUT	370	47.3	25	13	87	175	0	13	57	0
PASTURE	350	44.6	0	15	33	20	156	126	0	0
CROP	369	73.7	0	3	5	1	88	272	0	0
SOIL	1006	66.1	0	0	6	307	24	2	665	2
WATER	300	86.3	0	3	0	33	0	1	4	259
TOTAL	10557		1291	6326	434	710	279	530	726	261

OVERALL PERFORMANCE = 8494/10,557 = 80.5%

AVERAGE PERFORMANCE BY COVER CLASS = 532.4/8 = 66.6%

Table 3. Waveband Evaluation Classification Results Using Channels 1, 3, & 6 (the best 3). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	94.7	734	5	6	22	1	6	0	1
HARDWOOD	7269	77.8	660	5658	731	100	70	49	0	1
TUPELO	118	21.2	50	6	25	34	1	2	0	0
CLEARCUT	370	68.1	62	0	0	252	12	14	30	0
PASTURE	350	62.3	16	2	23	85	218	6	0	0
CROP	369	61.5	0	1	9	65	67	227	0	0
SOIL	1006	89.8	0	0	1	88	11	0	903	3
WATER	300	88.0	1	3	0	28	0	0	4	264
TOTAL	10557		1523	5675	795	674	380	304	937	269

OVERALL PERFORMANCE = 8281/10,557 = 78.4%

AVERAGE PERFORMANCE BY COVER CLASS = 563.4/8 = 70.4%

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Table 4. Waveband Evaluation Classification Results Using Channels 2, 4, 5, & 7 (the best 4). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	91.0	705	4	0	40	26	0	0	0
HARDWOOD	7269	91.1	114	6621	140	320	62	12	0	0
TUPELO	118	58.5	0	4	69	7	5	32	0	1
CLEARCUT	370	60.5	48	0	0	224	49	0	49	0
PASTURE	350	82.6	0	2	1	38	289	20	0	0
CROP	369	79.7	0	1	8	2	64	294	0	0
SOIL	1006	85.6	0	0	0	123	19	0	861	3
WATER	300	78.7	0	3	2	55	1	0	3	236
TOTAL	10557		867	6635	220	809	515	358	913	240

OVERALL PERFORMANCE = 9299/10,557 = 88.1%

AVERAGE PERFORMANCE BY COVER CLASS = 627.7/8 = 78.5%

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Table 5. Waveband Evaluation Classification Results Using Channels 2, 3, 4, 6, & 7 (the best 5). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	93.8	727	1	0	27	19	1	0	0
HARDWOOD	7269	90.9	280	6609	133	180	64	2	0	1
TUPELO	118	66.1	0	11	78	5	23	1	0	0
CLEARCUT	370	61.6	47	0	0	288	22	0	73	0
PASTURE	350	80.6	1	2	0	46	282	19	0	0
CROP	369	79.9	0	0	0	1	83	295	0	0
SOIL	1006	86.2	0	0	0	115	19	0	867	5
WATER	300	80.7	0	4	0	48	3	0	3	242
TOTAL	10557		1055	6627	211	650	515	308	943	248

OVERALL PERFORMANCE = 9318/10,557 = 88.3%

AVERAGE PERFORMANCE BY COVER CLASS = 639.8/8 = 80.0%

Table 6. Waveband Evaluation Classification Results Using Channels 1, 2, 4, 5, 6, & 7 (the best 6). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	93.0	721	4	0	16	34	0	0	0
HARDWOOD	7269	92.7	125	6739	115	174	110	4	0	2
TUPELO	118	57.6	0	13	68	9	0	28	0	0
CLEARCUT	370	59.2	77	0	0	219	39	0	35	0
PASTURE	350	85.7	0	3	0	33	300	14	0	0
CROP	369	78.9	0	10	0	1	67	291	0	0
SOIL	1006	90.4	0	1	0	67	25	0	909	4
WATER	300	81.3	0	5	0	45	1	0	5	244
TOTAL	10557		923	6775	183	564	576	337	949	250

OVERALL PERFORMANCE = 9491/10,557 = 89.9%

AVERAGE PERFORMANCE BY COVER CLASS = 638.8/8 = 79.9%

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Table 7. Waveband Evaluation Classification Results Using All 7 Channels. (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	95.0	736	2	0	11	25	0	1	0
HARDWOOD	7269	93.2	126	6774	113	128	127	0	0	1
TUPELO	118	67.8	0	19	80	16	1	2	0	0
CLEARCUT	370	64.9	80	0	0	240	19	0	31	0
PASTURE	350	83.4	0	3	0	36	292	19	0	0
CROP	369	81.0	0	0	0	1	69	299	0	0
SOIL	1006	90.6	0	1	0	64	23	0	911	7
WATER	300	81.7	0	5	0	47	0	0	3	245
TOTAL	10557		942	6804	193	543	556	320	946	253

OVERALL PERFORMANCE = 9577/10,557 = 90.7%

AVERAGE PERFORMANCE BY COVER CLASS = 657.6/8 = 82.2%

Table 8. Waveband Evaluation Classification Results Using Visible Channels (1, 2, & 3). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	92.1	714	15	0	31	4	6	0	5
HARDWOOD	7269	84.6	652	6151	163	209	1	61	0	32
TUPELO	118	66.1	1	3	78	5	4	27	0	0
CLEARCUT	370	47.6	90	0	0	176	35	6	35	28
PASTURE	350	38.0	9	11	7	31	133	126	0	33
CROP	369	65.0	0	2	11	30	50	240	0	36
SOIL	1006	86.3	0	0	1	115	22	0	868	0
WATER	300	63.3	2	3	0	57	41	1	6	190
TOTAL	10557		1468	6185	260	654	290	467	909	324

OVERALL PERFORMANCE = 8550/10,557 = 81.0%

AVERAGE PERFORMANCE BY COVER CLASS = 543/8 = 67.9%

Table 9. Waveband Evaluation Classification Results Using Reflective IR Channels (4, 5, & 6). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	91.2	707	1	0	33	29	5	0	0
HARDWOOD	7269	69.5	99	5055	700	214	337	862	0	2
TUPELO	118	30.5	0	19	36	11	3	49	0	0
CLEARCUT	370	47.3	67	0	0	175	65	0	51	12
PASTURE	350	71.7	0	19	3	49	251	28	0	0
CROP	369	69.6	0	0	16	2	94	257	0	0
SOIL	1006	85.7	1	0	0	125	17	0	862	1
WATER	300	84.0	0	1	1	41	1	2	2	252
TOTAL	10557		874	5095	756	650	797	1203	915	267

OVERALL PERFORMANCE = 7595/10,557 = 71.9%

AVERAGE PERFORMANCE BY COVER CLASS = 549.5/8 = 68.7%

Table 10. Waveband Evaluation Classification Results Using Best 3 Channels Minus the Middle IR Channels (3, 4, & 5). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	87.1	675	2	0	58	29	1	0	0
HARDWOOD	7269	88.6	77	6437	352	376	22	5	0	0
TUPELO	118	58.5	0	10	69	7	1	31	0	0
CLEARCUT	370	36.5	66	0	0	135	105	1	49	14
PASTURE	350	76.0	0	17	14	38	266	15	0	0
CROP	369	74.3	0	0	1	2	92	274	0	0
SOIL	1006	89.2	0	0	0	96	8	1	897	4
WATER	300	87.7	0	2	2	28	0	1	4	263
TOTAL	10557		818	6468	438	750	523	329	950	281

OVERALL PERFORMANCE = 9016/10,557 = 85.4%

AVERAGE PERFORMANCE BY COVER CLASS = 597.9/8 = 74.7%

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Table 11. Waveband Evaluation[1] Classification Results Using Channels 2, 4, & 5 (the best 3 selected by D[AVE][1]). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	91.2	707	3	1	41	23	0	0	0
HARDWOOD	7269	91.7	111	6666	142	324	15	11	0	0
TUPELO	118	34.7	0	4	41	8	1	64	0	0
CLEARCUT	370	42.7	71	0	0	158	103	0	30	8
PASTURE	350	64.0	0	44	15	55	224	12	0	0
CROP	369	71.3	0	0	52	3	51	263	0	0
SOIL	1006	85.4	0	0	0	127	14	1	859	5
WATER	300	85.0	0	3	2	37	0	1	2	255
TOTAL	10557		889	6720	253	753	431	352	891	268

OVERALL PERFORMANCE = 9173/10,557 = 86.9%

AVERAGE PERFORMANCE BY COVER CLASS = 566.1/8 = 70.8%

[1] Except for this table and Table 25, all other tables in Appendix A were based on channels selected using the Minimum Divergence (D[Min]) separability criterion.

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Table 12. Waveband Evaluation Classification Results Using Channels 2, 3, 4, & 5 (simulated Landsat). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	92.6	718	4	0	35	16	0	0	2
HARDWOOD	7269	91.8	121	6674	167	285	17	5	0	0
TUPELO	118	78.0	0	8	92	7	8	2	0	1
CLEARCUT	370	51.4	81	0	0	190	77	1	15	6
PASTURE	350	71.1	0	28	0	49	249	24	0	0
CROP	369	79.1	0	0	0	2	74	292	0	1
SOIL	1006	90.3	0	0	0	76	15	0	908	7
WATER	300	86.3	0	4	0	32	1	2	2	259
TOTAL	10557		920	6718	259	676	457	326	925	276

OVERALL PERFORMANCE = 9382/10,557 = 88.9%

AVERAGE PERFORMANCE BY COVER CLASS = 640.6/8 = 80.1%

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Table 13. Waveband Evaluation Classification Results Using Channels 3, 5, 6, & 7 (one channel from each wavelength region). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	89.5	694	0	4	54	22	1	0	0
HARDWOOD	7269	85.7	408	6229	334	243	51	3	0	1
TUPELO	118	46.6	4	25	55	9	20	5	0	0
CLEARCUT	370	63.0	56	0	0	233	23	0	53	5
PASTURE	350	74.9	22	1	1	44	262	20	0	0
CROP	369	73.7	1	4	6	1	85	272	0	0
SOIL	1006	84.2	0	0	0	112	44	0	847	3
WATER	300	86.3	1	3	1	33	1	0	2	259
TOTAL	10557		1186	6262	401	729	508	301	902	268

OVERALL PERFORMANCE = 8851/10,557 = 83.4%

AVERAGE PERFORMANCE BY COVER CLASS = 603.9/8 = 75.5%

Table 14. Waveband Evaluation Classification Results Using Channels 2, 4, 6, & 7 (one channel from each wavelength region). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	92.3	715	4	1	34	21	0	0	0
HARDWOOD	7269	90.7	273	6591	115	229	55	4	0	2
TUPELO	118	42.4	0	7	50	7	45	9	0	0
CLEARCUT	370	58.6	52	0	0	217	29	0	72	0
PASTURE	350	82.3	0	2	0	43	288	17	0	0
CROP	369	71.5	0	4	21	0	80	264	0	0
SOIL	1006	81.0	0	0	0	170	20	0	815	1
WATER	300	81.0	0	4	2	44	2	0	5	243
TOTAL	10557		1040	6612	189	744	540	294	892	246

OVERALL PERFORMANCE = 9183/10,557 = 87.0%

AVERAGE PERFORMANCE BY COVER CLASS = 599.8/8 = 75.0%

Table 15. Waveband Evaluation Classification Results Using Channels 2 & 5 (the best 2). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	82.1	636	46	83	2	7	1	0	0
HARDWOOD	7269	86.8	643	6313	132	19	29	133	0	0
TUPELO	118	24.6	18	3	29	3	18	47	0	0
CLEARCUT	370	20.3	79	11	88	75	3	32	81	1
PASTURE	350	52.3	9	41	7	3	183	107	0	0
CROP	369	52.0	1	17	0	0	159	192	0	0
SOIL	1006	91.0	13	0	2	2	7	66	915	1
WATER	300	86.3	4	2	0	26	0	2	7	259
TOTAL	10557		1403	6433	341	130	406	580	1003	261

OVERALL PERFORMANCE = 8602/10,557 = 81.5%

AVERAGE PERFORMANCE BY COVER CLASS = 495.4/8 = 61.9%

Table 16. Waveband Evaluation Classification Results Using Channels 1, 3, & 5 (the best 3). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	83.5	647	12	103	0	2	10	1	0
HARDWOOD	7269	76.1	511	5533	258	17	472	476	2	0
TUPELO	118	48.3	17	17	57	0	11	16	0	0
CLEARCUT	370	30.3	124	0	0	112	6	25	94	9
PASTURE	350	44.0	26	10	30	5	154	119	6	0
CROP	369	90.0	1	0	0	0	36	332	0	0
SOIL	1006	92.0	3	0	1	7	7	62	926	0
WATER	300	86.0	3	3	0	28	0	1	7	258
TOTAL	10557		1332	5575	449	169	688	1041	1036	267

OVERALL PERFORMANCE = 8019/10,557 = 76.0%

AVERAGE PERFORMANCE BY COVER CLASS = 550.2/8 = 68.8%

Table 17. Waveband Evaluation Classification Results Using Channels 1, 3, 4, & 6 (the best 4). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	91.9	712	7	43	10	3	0	0	0
HARDWOOD	7269	88.4	325	6423	267	8	154	91	1	0
TUPELO	118	62.7	8	31	74	0	1	4	0	0
CLEARCUT	370	41.9	103	0	0	155	15	0	95	2
PASTURE	350	51.4	18	13	31	6	180	100	2	0
CROP	369	99.2	2	1	0	0	0	366	0	0
SOIL	1006	91.3	7	0	0	5	13	63	918	0
WATER	300	87.3	7	2	0	21	0	2	6	262
TOTAL	10557		1182	6477	415	205	366	626	1022	264

OVERALL PERFORMANCE = 9090/10,557 = 86.1%

AVERAGE PERFORMANCE BY COVER CLASS = 614.1/8 = 76.8%

Table 18. Waveband Evaluation Classification Results Using Channels 1, 2, 3, 4, & 6 (the best 5). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	94.5	732	9	17	10	7	0	0	0
HARDWOOD	7269	89.8	345	6526	111	12	188	86	1	0
TUPELO	118	81.4	6	15	96	0	1	0	0	0
CLEARCUT	370	44.1	97	0	0	163	16	0	94	0
PASTURE	350	56.0	16	19	1	8	196	107	3	0
CROP	369	98.9	2	1	0	0	0	365	1	0
SOIL	1006	91.3	7	0	0	8	12	61	918	0
WATER	300	85.7	8	2	0	25	0	2	6	0
TOTAL	10557		1213	6572	225	226	420	621	1023	257

OVERALL PERFORMANCE = 9253/10,557 = 87.6%

AVERAGE PERFORMANCE BY COVER CLASS = 641.7/8 = 80.2%

Table 19. Waveband Evaluation Classification Results Using Channels 1, 3, 4, 5, 6, & 7 (the best 6). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	92.9	720	8	27	8	11	0	1	0
HARDWOOD	7269	89.7	340	6522	208	15	94	88	2	0
TUPELO	118	78.8	6	18	93	0	1	0	0	0
CLEARCUT	370	43.5	108	0	0	161	17	5	79	0
PASTURE	350	60.0	31	5	0	5	210	73	26	0
CROP	369	97.6	1	1	0	0	1	360	6	0
SOIL	1006	89.8	12	1	0	15	17	58	903	0
WATER	300	87.7	6	2	0	21	0	2	6	0
TOTAL	10557		1224	6557	328	225	351	586	1023	263

OVERALL PERFORMANCE = 9232/10,557 = 87.4%

AVERAGE PERFORMANCE BY COVER CLASS = 640/8 = 80.0%

Table 20. Waveband Evaluation Classification Results Using All 7 Channels. (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	93.3	723	90	25	8	10	0	0	0
HARDWOOD	7269	91.1	367	6621	96	16	100	69	0	0
TUPELO	118	83.9	6	12	99	0	1	0	0	0
CLEARCUT	370	45.7	103	0	0	169	15	1	82	0
PASTURE	350	61.4	31	6	0	9	215	75	14	0
CROP	369	98.6	2	1	0	0	1	364	1	0
SOIL	1006	90.8	14	1	0	15	12	51	913	0
WATER	300	86.7	6	2	0	25	0	2	5	260
TOTAL	10557		1252	6652	220	242	354	562	1015	260

OVERALL PERFORMANCE = 9364/10,557 = 88.7%

AVERAGE PERFORMANCE BY COVER CLASS = 651.5/8 = 81.4%

Table 21. Waveband Evaluation Classification Results Using Visible Channels (1, 2, & 3). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	90.7	703	17	20	3	27	1	0	4
HARDWOOD	7269	74.9	1058	5446	519	78	31	134	1	2
TUPELO	118	76.3	1	10	90	0	4	13	0	0
CLEARCUT	370	35.4	122	0	0	131	11	6	94	6
PASTURE	350	40.0	7	34	3	2	140	106	0	58
CROP	369	53.4	67	0	2	1	27	197	0	75
SOIL	1006	85.3	1	1	0	12	6	128	858	0
WATER	300	18.3	62	2	0	55	109	6	11	55
TOTAL	10557		2021	5510	634	282	355	591	964	200

OVERALL PERFORMANCE = 7620/10,557 = 72.2%

AVERAGE PERFORMANCE BY COVER CLASS = 474.3/8 = 59.3%

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Table 22. Waveband Evaluation Classification Results Using Reflective IR Channels (4, 5, & 6). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	93.8	727	1	8	7	27	0	5	0
HARDWOOD	7269	57.0	546	4142	273	15	101	2188	3	1
TUPELO	118	55.9	6	10	66	0	1	35	0	0
CLEARCUT	370	34.6	91	0	1	128	9	0	130	11
PASTURE	350	50.0	16	15	8	0	175	99	37	0
CROP	369	97.3	1	0	0	0	3	359	6	0
SOIL	1006	96.4	12	0	0	9	6	9	970	0
WATER	300	85.3	9	0	0	27	0	4	4	256
TOTAL	10557		1408	4168	356	186	322	2694	1155	268

OVERALL PERFORMANCE = 6823/10,557 = 64.6%

AVERAGE PERFORMANCE BY COVER CLASS = 570.3/8 = 71.3%

Table 23. Waveband Evaluation Classification Results Using the Best 3 Channels Minus the Near IR Channels (2, 3, & 6). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	89.8	696	10	3	31	28	7	0	0
HARDWOOD	7269	85.1	302	6188	585	16	77	101	0	0
TUPELO	118	61.0	1	3	72	0	1	41	0	0
CLEARCUT	370	36.8	78	0	0	136	39	14	103	0
PASTURE	350	57.1	17	26	9	1	200	95	2	0
CROP	369	82.9	6	23	29	0	3	306	2	0
SOIL	1006	79.2	6	0	0	2	3	197	797	1
WATER	300	89.3	3	3	0	18	0	2	6	268
TOTAL	10557		1109	6253	698	204	351	763	910	269

OVERALL PERFORMANCE = 8663/10,557 = 82.1%

AVERAGE PERFORMANCE BY COVER CLASS = 581.2/8 = 72.7%

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Table 24. Waveband Evaluation Classification Results Using the Best 3 Channels Minus the Reflective IR Channels (1, 2, & 7). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	38.5	298	197	41	7	129	35	67	1
HARDWOOD	7269	63.5	1755	4616	478	76	39	300	3	2
TUPELO	118	72.9	0	10	86	0	0	22	0	0
CLEARCUT	370	35.4	100	5	0	131	44	20	58	12
PASTURE	350	69.4	32	18	0	5	243	35	16	1
CROP	369	68.8	32	0	0	1	5	254	2	75
SOIL	1006	91.0	2	1	0	46	20	19	915	3
WATER	300	63.0	14	4	0	76	0	3	14	189
TOTAL	10557		2233	4851	605	342	480	688	1075	283

OVERALL PERFORMANCE = 6786/10,557 = 64.3%

AVERAGE PERFORMANCE BY COVER CLASS = 502.5/8 = 62.8%

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Table 25. Waveband Evaluation Classification Results Using Channels 3, 4, & 7 (the best 3 selected by D[AVE]). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	64.1	497	2	20	9	247	0	0	0
HARDWOOD	7269	87.9	389	6393	117	13	234	123	0	0
TUPELO	118	66.1	8	25	78	0	1	6	0	0
CLEARCUT	370	35.7	91	0	0	132	42	0	95	10
PASTURE	350	72.3	10	18	2	0	253	63	3	1
CROP	369	98.4	0	1	0	0	2	363	3	0
SOIL	1006	92.9	7	0	1	28	8	26	935	1
WATER	300	85.7	6	2	0	22	0	2	11	257
TOTAL	10557		1008	6441	218	204	787	583	1047	269

OVERALL PERFORMANCE = 8908/10,557 = 84.4%

AVERAGE PERFORMANCE BY COVER CLASS = 603.1/8 = 75.4%

Table 26. Waveband Evaluation Classification Results Using Channels 2, 3, 4, & 5 (simulated Landsat). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	94.1	729	3	8	9	26	0	0	0
HARDWOOD	7269	90.1	466	6548	48	15	92	100	0	0
TUPELO	118	82.2	5	15	97	0	1	0	0	0
CLEARCUT	370	37.8	116	0	0	140	11	0	101	2
PASTURE	350	51.1	21	38	0	0	179	110	2	0
CROP	369	99.2	1	1	0	0	0	366	1	0
SOIL	1006	95.0	9	1	0	5	9	26	956	0
WATER	300	86.3	6	2	0	24	0	2	7	259
TOTAL	10557		1353	6608	153	193	318	604	1067	261

OVERALL PERFORMANCE = 9274/10,557 = 87.8%

AVERAGE PERFORMANCE BY COVER CLASS = 635.8/8 = 79.5%

Table 27. Waveband Evaluation Classification Results Using Channels 3, 5, 6, & 7 (one channel from each wavelength region). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	93.7	726	4	20	8	15	1	1	0
HARDWOOD	7269	86.4	445	6279	187	17	229	111	1	0
TUPELO	118	71.2	6	27	84	0	1	0	0	0
CLEARCUT	370	41.4	93	0	0	153	23	1	100	0
PASTURE	350	67.1	39	2	1	0	235	66	7	0
CROP	369	98.1	1	1	0	0	1	362	4	0
SOIL	1006	90.4	16	0	1	40	8	3	909	1
WATER	300	87.3	4	2	0	23	0	2	7	262
TOTAL	10557		1330	6315	293	241	512	574	1029	263

OVERALL PERFORMANCE = 9010/10,557 = 85.3%

AVERAGE PERFORMANCE BY COVER CLASS = 635.5/8 = 79.4%

Table 28. Waveband Evaluation Classification Results Using Channels 2, 4, 6, & 7 (one channel from each wavelength region). (1979 TMS Data, MCB Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	92.3	715	1	16	8	34	0	1	0
HARDWOOD	7269	87.9	430	6393	63	13	247	120	3	0
TUPELO	118	79.7	7	14	94	0	2	1	0	0
CLEARCUT	370	40.3	89	0	0	149	29	0	103	0
PASTURE	350	69.1	25	7	0	1	242	71	4	0
CROP	369	98.1	1	1	0	0	3	362	2	0
SOIL	1006	90.0	8	0	0	48	14	30	905	1
WATER	300	85.3	6	2	0	28	0	2	6	256
TOTAL	10557		1281	6418	173	247	571	586	1024	257

OVERALL PERFORMANCE = 9116/10,557 = 86.4%

AVERAGE PERFORMANCE BY COVER CLASS = 642.7/8 = 80.3%

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Table 29. Statistical comparison among overall classification results for the GML algorithm using various three channel subsets and based upon the 1979 supervised training statistics and sample block test data.

	Channel[2/] Subset and	Table Location	% Correct	No. of Samples	Significant Differences[1/]
	(1,3,6)	(Table 3)	78.4		
	(1,2,3)	(Table 8)	81.0		
Overall Classification Performance	(4,5,6)	(Table 9)	71.9	10,557	All
	(3,4,5)	(Table 10)	85.4		
	(2,4,5)	(Table 11)	86.9		

[1/] Channel combinations which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

[2/] Description of the three channel subsets:

(1,3,6) = the "best 3" channel subset as determined by TD(MIN).
(⊕best 3 - Thermal IR)
(⊕best 3 - Near IR)

(1,2,3) = visible channels, and "Best 3" minus Reflective IR

(4,5,6) = reflective IR channels

(3,4,5) = "Best 3" channels minus Middle IR channels

(2,4,5) = the "best 3" channel subset as determined by TD(AVE).

Table 30. Statistical comparison among classification results by cover class for the GML algorithm using various three channel subsets and based upon the 1979 supervised training statistics and sample block test data.

Cover Class	Channel Subset and	Table Location	% Correct	No. of Samples	Significant Differences[1/]
PINE	(1,3,6)	(Table 3)	94.7	775	(3,4,5)/All
	(1,2,3)	(Table 8)	92.1		(4,5,6)/(1,3,6)
	(4,5,6)	(Table 9)	91.2		(1,2,3)/(1,3,6)
	(3,4,5)	(Table 10)	87.1		
	(2,4,5)	(Table 11)	91.2		
HDWD	(1,3,6)	Same as above	77.8	7269	All
	(1,2,3)		84.6		
	(4,5,6)		69.5		
	(3,4,5)		88.6		
	(2,4,5)		91.7		
TUPE	(1,3,6)	Same as above	21.2	118	(1,3,6)/(2,4,5);(3,4,5);(1,2,3)
	(1,2,3)		66.1		(4,5,6)/(3,4,5) & (1,2,3)
	(4,5,6)		30.5		(2,4,5)/(3,4,5) & (1,2,3)
	(3,4,5)		58.5		
	(2,4,5)		34.7		
CCUT	(1,3,6)	Same as above	68.1	370	(3,4,5)/All
	(1,2,3)		47.6		(2,4,5)/(1,3,6)
	(4,5,6)		47.3		(4,5,6)/(1,3,6)
	(3,4,5)		36.5		(1,2,3)/(1,3,6)
	(2,4,5)		42.7		
PAST	(1,3,6)	Same as above	62.3	350	(1,2,3)/All
	(1,2,3)		38.0		(1,3,6)/(4,5,6) & (3,4,5)
	(4,5,6)		71.7		(2,4,5)/(4,5,6) & (3,4,5)
	(3,4,5)		76.0		
	(2,4,5)		64.0		
CROP	(1,3,6)	Same as above	61.5	369	(1,3,6)/(4,5,6);(2,4,5);(3,4,5)
	(1,2,3)		65.0		(1,2,3)/(3,4,5)
	(4,5,6)		69.6		
	(3,4,5)		74.3		
	(2,4,5)		71.3		
SOIL	(1,3,6)	Same as above	89.8	1006	(2,4,5)/(3,4,5) & (1,3,6)
	(1,2,3)		86.3		(4,5,6)/(3,4,5) & (1,3,6)
	(4,5,6)		85.7		(1,2,3)/(3,4,5) & (1,3,6)
	(3,4,5)		89.2		
	(2,4,5)		85.4		
WATER	(1,3,6)	Same as above	88.0	300	(1,2,3)/All
	(1,2,3)		63.3		
	(4,5,6)		84.0		
	(3,4,5)		87.7		
	(2,4,5)		85.0		

[1/] Channel combinations that are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

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Table 31. Statistical comparison among overall classification results for the GML algorithm using various three channel subsets and based upon the 1979 MCB training statistics and sample block test data.

	Channel Subset[2] and	Table Location	% Correct	No. of Samples	Significant Differences[1]
Overall Classification Performance	(1,3,5)	(Table 16)	76.0	10,557	(1,2,7)/(1,2,3);(1,3,5);(2,3,6);(3,4,7)
	(1,2,3)	(Table 21)	72.2		(4,5,6)/(1,2,3);(1,3,5);(2,3,6);(3,4,7)
	(4,5,6)	(Table 22)	64.6		(1,2,3)/(1,3,5);(2,3,6)
	(2,3,6)	(Table 23)	82.1		
	(1,2,7)	(Table 24)	64.3		
	(3,4,7)	(Table 25)	84.4		

[1] Channel combinations which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

[2] Description of the three channel subsets:

(1,3,5) = the "best 3" channel subset as determined by TD(MIN); in addition to the "best 3" channel subsets minus the Thermal IR and Middle IR channels, respectively

(1,2,3) = Visible channels

(4,5,6) = Reflective IR channels

(2,3,6) = "Best 3" channel subset minus the Near IR channels

(1,2,7) = "Best 3" channel subset minus the Reflective IR channels

(3,4,7) = the "best 3" channel subset as determined by TD(AVE)

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Table 32. Statistical comparison among classification results by cover class for the GML algorithm using various three channel subsets and based upon the 1979 MCB training statistics and sample block test data.

Cover Class	Channel Subset and	Table Location	% Correct	No. of Samples	Significant Differences[1/]
PINE	(1,3,5)	(Table 16)	83.5	775	(1,2,7)/All
	(1,2,3)	(Table 21)	90.7		(3,4,7)/All
	(4,5,6)	(Table 22)	93.8		(1,3,5)/All
	(2,3,6)	(Table 23)	89.8		(2,3,6)/(4,5,6)
	(1,2,7)	(Table 24)	38.5		(1,2,3)/(4,5,6)
	(3,4,7)	(Table 25)	64.1		
HDWD	(1,3,5)	Same as above	76.1	7269	All
	(1,2,3)		74.9		
	(4,5,6)		57.0		
	(2,3,6)		85.1		
	(1,2,7)		63.5		
	(3,4,7)		87.9		
TUPE	(1,3,5)	Same as above	48.3	118	(1,3,5)/(3,4,7);(1,2,7);(1,2,3)
	(1,2,3)		76.3		(4,5,6)/(1,2,7);(1,2,3)
	(4,5,6)		55.9		(2,3,6)/(1,2,3)
	(2,3,6)		61.0		
	(1,2,7)		72.9		
	(3,4,7)		66.1		
CCUT	(1,3,5)	Same as above	30.3	370	None
	(1,2,3)		35.4		
	(4,5,6)		34.6		
	(2,3,6)		36.8		
	(1,2,7)		35.4		
	(3,4,7)		35.7		
PAST	(1,3,5)	Same as above	44.0	350	(1,2,3)/(4,5,6);(2,3,6);(1,2,7);(3,4,7)
	(1,2,3)		40.0		(1,3,5)/(2,3,6);(1,2,7);(3,4,7)
	(4,5,6)		50.0		(4,5,6)/(2,3,6);(1,2,7);(3,4,7)
	(2,3,6)		57.1		(2,3,6)/(1,2,7);(3,4,7)
	(1,2,7)		69.4		
	(3,4,7)		72.3		
CROP	(1,3,5)	Same as above	90.0	369	(1,2,3)/All
	(1,2,3)		53.4		(1,2,7)/All
	(4,5,6)		97.3		(2,3,6)/All
	(2,3,6)		82.9		(1,3,5)/All
	(1,2,7)		68.8		
	(3,4,7)		98.4		

Cover Class	Channel Subset and	Table Location	% Correct	No. of Samples	Significant Differences
SOIL	(1,3,5)	(Table 16)	92.0	1006	(2,3,6)/All
	(1,2,3)	(Table 21)	85.3		(1,2,3)/All
	(4,5,6)	(Table 22)	96.4		(1,2,7)/(4,5,6)
	(2,3,6)	(Table 23)	79.2		(1,3,5)/(4,5,6)
	(1,2,7)	(Table 24)	91.0		(3,4,7)/(4,5,6)
	(3,4,7)	(Table 25)	92.9		
WATER	(1,3,5)	Same as above	86.0	300	(1,2,3)/All
	(1,2,3)		18.3		(1,2,7)/All
	(4,5,6)		85.3		
	(2,3,6)		89.3		
	(1,2,7)		63.0		
	(3,4,7)		85.7		

1/Channel combinations that are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

C-3

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Table 33. Statistical comparison among overall classification results for the GML algorithm using various four channel subsets and based upon the 1979 supervised training statistics and sample block test data.

	Channel[2/] Subset and	Table Location	% Correct	No. of Samples	Significant Differences[1/]
	(2,4,5,7)	(Table 4)	88.1		
Overall Classification Performance	(2,3,4,5)	(Table 12)	88.9	10,557	All are significantly different
	(3,5,6,7)	(Table 13)	83.4		
	(2,4,6,7)	(Table 14)	87.0		

[1/] Channel combinations that are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

[2/] Description of the four channel subsets:

(2,4,5,7) = the "best 4" channel subset as determined by TD(MIN)

(2,3,4,5) = Simulated Landsat channels

(3,5,6,7)
(2,4,6,7) = Both are four channel subsets with one channel from each wavelength region

Table 34. Statistical comparison among classification results by cover class for the GML algorithm using various four channel subsets and based upon the 1979 supervised training statistics and sample block test data.

Cover Class	Channel Subset and	Table Location	% Correct	No. of Samples	Significant Differences[1]
PINE	(2,4,5,7)	(Table 4)	91.0	775	None
	(2,3,4,5)	(Table 12)	92.6		
	(3,5,6,7)	(Table 13)	89.5		
	(2,4,6,7)	(Table 14)	92.3		
HDWD	(2,4,5,7)	Same as above	91.1	7269	(3,5,6,7)/All
	(2,3,4,5)		91.8		(2,4,6,7)/(2,3,4,5)
	(3,5,6,7)		85.7		
	(2,4,6,7)		90.7		
TUPE	(2,4,5,7)	Same as above	58.5	118	(2,4,6,7)/(2,4,5,7) & (2,3,4,5)
	(2,3,4,5)		78.0		(3,5,6,7)/(2,4,5,7) & (2,3,4,5)
	(3,5,6,7)		46.6		(2,4,5,7)/(2,3,4,5)
	(2,4,6,7)		42.4		
CCUT	(2,4,5,7)	Same as above	60.5	370	(2,3,4,5)/All
	(2,3,4,5)		51.4		
	(3,5,6,7)		63.0		
	(2,4,6,7)		58.6		
PAST	(2,4,5,7)	Same as above	82.6	350	(2,3,4,5)/(2,4,6,7) & (2,4,5,7)
	(2,3,4,5)		71.1		(3,5,6,7)/(2,4,6,7) & (2,4,5,7)
	(3,5,6,7)		74.9		
	(2,4,6,7)		82.3		
CROP	(2,4,5,7)	Same as above	79.7	369	(2,4,6,7)/(2,3,4,5) & (2,4,5,7)
	(2,3,4,5)		79.1		(3,5,6,7)/(2,3,4,5)
	(3,5,6,7)		73.7		
	(2,4,6,7)		71.5		
SOIL	(2,4,5,7)	Same as above	85.6	1006	(2,4,6,7)/All
	(2,3,4,5)		90.3		(3,5,6,7)/(2,3,4,5)
	(3,5,6,7)		84.2		(2,4,5,7)/(2,3,4,5)
	(2,4,6,7)		81.0		
WATER	(2,4,5,7)	Same as above	88.1	10,557	All
	(2,3,4,5)		88.9		
	(3,5,6,7)		83.4		
	(2,4,6,7)		87.0		

[1] Channel combinations that are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 35. Statistical comparison among overall classification results for the GML algorithm using various four channel subsets and based upon the 1979 MCB training statistics and sample block test data.

	Channel Subset[2/] and	Table Location	% Correct	No. of Samples	Significant Differences[1/]
	(1,3,4,6)	(Table 17)	86.1		(3,5,6,7)/All
Overall Classification Performance	(2,3,4,5)	(Table 26)	87.8	10,557	(1,3,4,6)/(2,3,4,5)
	(3,5,6,7)	(Table 27)	85.3		(2,4,6,7)/(2,3,4,5)
	(2,4,6,7)	(Table 28)	86.4		

[1/] Channel combinations that are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

[2/] Description of the four channel subsets:

(1,3,4,6) = the "best 4" channel subset as determined by TD(MIN)

(2,3,4,5) = Simulated Landsat channels

(3,5,6,7)
(2,4,6,7) = Both are four channel subsets with one channel from each wavelength region

Table 36. Statistical comparison among classification results by cover class for the GML algorithm using various four channel subsets and based upon the 1979 MCB training statistics and sample block test data.

Cover Class	Channel Subset and	Table Location	% Correct	No. of Samples	Significant Differences[1]
PINE	(1,3,4,6)	(Table 17)	91.9	775	None
	(2,3,4,5)	(Table 26)	94.1		
	(3,5,6,7)	(Table 27)	93.7		
	(2,4,6,7)	(Table 28)	92.3		
HDWD	(1,3,4,6)	Same as above	88.4	7269	(3,5,6,7)/All
	(2,3,4,5)		90.1		(2,4,6,7)/(2,3,4,5)
	(3,5,6,7)		86.4		(1,3,4,6)/(2,3,4,5)
	(2,4,6,7)		87.9		
TUPE	(1,3,4,6)	Same as above	62.7	118	(1,3,4,6)/(2,4,6,7) & (2,3,4,5)
	(2,3,4,5)		82.2		
	(3,5,6,7)		71.2		
	(2,4,6,7)		79.7		
CCUT	(1,3,4,6)	Same as above	41.9	370	None
	(2,3,4,5)		37.8		
	(3,5,6,7)		41.4		
	(2,4,6,7)		40.3		
PAST	(1,3,4,6)	Same as above	51.4	350	(2,3,4,5)/(3,5,6,7) & (2,4,6,7)
	(2,3,4,5)		51.1		(1,3,4,6)/(3,5,6,7) & (2,4,6,7)
	(3,5,6,7)		67.1		
	(2,4,6,7)		69.1		
CROP	(1,3,4,6)	Same as above	99.2	369	None
	(2,3,4,5)		99.2		
	(3,5,6,7)		98.1		
	(2,4,6,7)		98.1		
SOIL	(1,3,4,6)	Same as above	91.3	1006	(2,4,6,7)/(2,3,4,5)
	(2,3,4,5)		95.0		(3,5,6,7)/(2,3,4,5)
	(3,5,6,7)		90.4		(1,3,4,6)/(2,3,4,5)
	(2,4,6,7)		90.4		
WATER	(1,3,4,6)	Same as above	87.3	300	None
	(2,3,4,5)		86.3		
	(3,5,6,7)		87.3		
	(2,4,6,7)		85.3		

[1] Channel combinations that are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

APPENDIX B (Tables 37-77)

Comparisons Among Classification Algorithms (L2, GML and SECHO)

for both the 1979 and 1980 TMS Data Set

Table 37. Summary table of overall classification results for the L2, GML and SECHO classifiers. (Untransformed 1979 and 1980 TMS data, Supervised and MCB training statistics, sample block test data).

I) 1979 Untransformed TMS Data

Training Statistics and Channel Combination	Classifier		
	L2	GML	SECHO
Supervised			
Best 4 (CH'S 2,4,5,7)	81.8%	88.1%	90.0%
All 7 Channels	85.3%	90.7%	91.6%
Multicluster Block			
Best 4 (CH'S 1,3,4,6)	77.4%	86.1%	90.6%
All 7 Channels	81.4%	88.7%	92.3%

II) 1980 Untransformed TMS Data

Training Statistics and Channel Combination	Classifier		
	L2	GML	SECHO
Supervised			
Best 4 (CH'S 1,2,3,6)	75.3%	82.8%	85.9%
All 8 Channels	77.5%	88.5%	89.6%
Multicluster Block			
Best 4 (CH'S 1,3,4,5)	67.6%	79.7%	84.6%
All 8 Channels	70.2%	79.8%	84.2%

Table 38. Classification Results Based Upon Supervised Training Statistics and the L-2 Minimum Distance Classifier, Using Channels 2, 4, 5, & 7 of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	85.5	663	8	2	85	6	8	3	0
HARDWOOD	7269	84.0	331	6103	347	72	66	350	0	0
TUPELO	118	55.1	7	16	65	0	0	30	0	0
CLEARCUT	370	68.6	59	0	7	254	9	1	37	3
PASTURE	350	70.9	3	3	1	29	248	66	0	0
CROP	369	88.1	0	10	1	1	32	325	0	0
SOIL	1006	71.6	12	0	5	195	71	3	720	0
WATER	300	85.7	7	0	3	23	0	3	7	257
TOTAL	10557		1082	6140	431	659	432	786	767	260

OVERALL PERFORMANCE = 10,557/8635 = 81.8%

AVERAGE PERFORMANCE BY COVER CLASS = 609.5/8 = 76.2%

Table 39. Classification Results Based Upon Supervised Training Statistics and the GML Classifier, Using Channels 2, 4, 5, & 7 (the best 4) of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	91.0	705	4	0	40	26	0	0	0
HARDWOOD	7269	91.1	114	6621	140	320	62	12	0	0
TUPELO	118	58.5	0	4	69	7	5	32	0	1
CLEARCUT	370	60.5	48	0	0	224	49	0	49	0
PASTURE	350	82.6	0	2	1	38	289	20	0	0
CROP	369	79.7	0	1	8	2	64	294	0	0
SOIL	1006	85.6	0	0	0	123	19	0	861	3
WATER	300	78.7	0	3	2	55	1	0	3	236
TOTAL	10557		867	6635	220	809	515	358	913	240

OVERALL PERFORMANCE = 9299/10,557 = 88.1%

AVERAGE PERFORMANCE BY COVER CLASS = 627.7/8 = 78.5%

Table 40. Classification Results Based Upon Supervised Training Statistics and the ECHO Classifier, Using Channels 2, 4, 5, & 7 of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	92.9	720	1	0	18	36	0	0	0
HARDWOOD	7269	93.7	73	6811	45	248	87	4	0	1
TUPELO	118	57.6	0	9	68	6	4	30	0	1
CLEARCUT	370	58.9	41	0	0	218	65	0	46	0
PASTURE	350	83.1	0	2	0	41	291	16	0	0
CROP	369	81.6	0	0	8	2	58	301	0	0
SOIL	1006	86.0	0	0	0	119	19	0	865	3
WATER	300	75.0	0	3	2	66	1	0	3	225
TOTAL	10557		834	6826	123	718	561	351	914	230

OVERALL PERFORMANCE = 9499/10,557 = 90.0%

AVERAGE PERFORMANCE BY COVER CLASS = 628.8/8 = 78.6%

Table 41. Classification Results Based Upon Supervised Training Statistics and the L-2 Minimum Distance Classifier, Using All 7 Channels of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	91.5	709	9	2	43	4	8	0	0
HARDWOOD	7269	88.2	343	6408	214	77	62	165	0	0
TUPELO	118	68.6	6	10	81	1	0	20	0	0
CLEARCUT	370	65.4	86	0	2	242	11	1	25	3
PASTURE	350	70.3	3	2	2	35	246	62	0	0
CROP	369	87.8	0	1	1	1	42	324	0	0
SOIL	1006	73.2	2	0	2	225	41	0	736	0
WATER	300	87.3	5	1	2	21	0	3	6	262
TOTAL	10557		1154	6431	306	645	406	583	767	265

OVERALL PERFORMANCE = 9008/10,557 = 85.3%

AVERAGE PERFORMANCE BY COVER CLASS = 632.3/8 = 79.0%

Table 42. Classification Results Based Upon Supervised Training Statistics and the GML Classifier, Using All 7 Channels of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	95.0	736	2	0	11	25	0	1	0
HARDWOOD	7269	93.2	126	6774	113	128	127	0	0	1
TUPELO	118	67.8	0	19	80	16	1	2	0	0
CLEARCUT	370	64.9	80	0	0	240	19	0	31	0
PASTURE	350	83.4	0	3	0	36	292	19	0	0
CROP	369	81.0	0	0	0	1	69	299	0	0
SOIL	1006	90.6	0	1	0	64	23	0	911	7
WATER	300	81.7	0	5	0	47	0	0	3	245
TOTAL	10557		942	6804	193	543	556	320	946	253

OVERALL PERFORMANCE = 9577/10,557 = 90.7%

AVERAGE PERFORMANCE BY COVER CLASS = 657.6/8 = 82.2%

Table 43. Classification Results Based Upon Supervised Training Statistics and the ECHO Classifier, Using All 7 Channels of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	94.7	734	0	0	15	25	0	1	0
HARDWOOD	7269	94.8	98	6893	57	86	134	0	0	1
TUPELO	118	65.3	0	22	77	16	1	2	0	0
CLEARCUT	370	64.6	80	0	0	239	20	0	31	0
PASTURE	350	84.6	0	2	0	34	296	18	0	0
CROP	369	81.0	0	0	0	1	69	299	0	0
SOIL	1006	90.6	0	1	0	64	23	0	911	7
WATER	300	81.3	0	5	0	48	0	0	3	244
TOTAL	10557		912	6923	134	503	568	319	946	252

OVERALL PERFORMANCE = 9693/10,577 = 91.6%

AVERAGE PERFORMANCE BY COVER CLASS = 656.9/8 = 82.1%

Table 44. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the L-2 Minimum Distance Classifier, Using Channels 1, 3, 4, & 6 of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	85.3	661	1	91	7	15	0	0	0
HARDWOOD	7269	76.8	170	5585	1090	3	100	321	0	0
TUPELO	118	47.5	6	52	56	0	0	4	0	0
CLEARCUT	370	31.9	120	0	2	118	14	0	97	19
PASTURE	350	50.6	9	24	34	1	177	105	0	0
CROP	369	97.0	1	1	0	0	8	358	1	0
SOIL	1006	93.9	4	0	2	10	10	34	945	1
WATER	300	88.7	9	1	0	14	0	4	6	266
TOTAL	10557		980	5664	1275	153	324	826	1049	286

OVERALL PERFORMANCE = 8166/10,557 = 77.4%

AVERAGE PERFORMANCE BY COVER CLASS = 571.7/8 = 71.5%

Table 45. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the GML Classifier, Using Channels 1, 3, 4, & 6 (the best 4) of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	91.9	712	7	43	10	3	0	0	0
HARDWOOD	7269	88.4	325	6423	267	8	154	91	1	0
TUPELO	118	62.7	8	31	74	0	1	4	0	0
CLEARCUT	370	41.9	103	0	0	155	15	0	95	2
PASTURE	350	51.4	18	13	31	6	180	100	2	0
CROP	369	99.2	2	1	0	0	0	366	0	0
SOIL	1006	91.3	7	0	0	5	13	63	918	0
WATER	300	87.3	7	2	0	21	0	2	6	262
TOTAL	10557		1182	6477	415	205	366	626	1022	264

OVERALL PERFORMANCE = 9090/10,557 = 86.1%

AVERAGE PERFORMANCE BY COVER CLASS = 614.1/8 = 76.8%

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Table 46. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the ECHO Classifier, Using Channels 1, 3, 4, & 6 of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	94.8	735	5	31	4	0	0	0	0
HARDWOOD	7269	94.7	66	6884	112	8	174	25	0	0
TUPELO	118	40.7	14	56	48	0	0	0	0	0
CLEARCUT	370	39.5	94	0	0	146	35	0	95	0
PASTURE	350	47.4	24	10	37	4	166	109	0	0
CROP	369	98.6	2	1	0	0	0	364	2	0
SOIL	1006	94.7	5	0	0	1	15	32	953	0
WATER	300	89.0	7	3	0	15	0	2	6	267
TOTAL	10557		947	6959	228	178	390	532	1056	267

OVERALL PERFORMANCE = 9563/10,557 = 90.6%

AVERAGE PERFORMANCE BY COVER CLASS = 599.4/8 = 74.9%

Table 47. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the L-2 Minimum Distance Classifier, Using All 7 Channels of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	89.3	692	5	47	8	23	0	0	0
HARDWOOD	7269	82.1	318	5968	707	11	57	208	0	0
TUPELO	118	58.5	8	38	69	0	0	3	0	0
CLEARCUT	370	35.1	111	0	1	130	15	0	93	20
PASTURE	350	66.0	10	5	3	0	231	100	1	0
CROP	369	98.6	1	1	0	0	3	364	0	0
SOIL	1006	87.1	6	0	2	62	26	33	876	1
WATER	300	87.3	6	2	0	21	0	3	6	262
TOTAL	10557		1152	6019	829	232	355	711	976	283

OVERALL PERFORMANCE = 8592/10,557 = 81.4%

AVERAGE PERFORMANCE BY COVER CLASS = 604/8 = 75.5%

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Table 48. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the GML Classifier, Using All 7 Channels of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	93.3	723	90	25	8	10	0	0	0
HARDWOOD	7269	91.1	367	6621	96	16	100	69	0	0
TUPELO	118	83.9	6	12	99	0	1	0	0	0
CLEARCUT	370	45.7	103	0	0	169	15	1	82	0
PASTURE	350	61.4	31	6	0	9	215	75	14	0
CROP	369	98.6	2	1	0	0	1	364	1	0
SOIL	1006	90.8	14	1	0	15	12	51	913	0
WATER	300	86.7	6	2	0	25	0	2	5	260
TOTAL	10557		1252	6652	220	242	354	562	1015	260

OVERALL PERFORMANCE = 9364/10,557 = 88.7%

AVERAGE PERFORMANCE BY COVER CLASS = 651.5/8 = 81.4%

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Table 49. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the ECHO Classifier, Using All 7 Channels of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	94.6	733	6	31	5	0	0	0	0
HARDWOOD	7269	96.1	107	6989	24	6	124	19	0	0
TUPELO	118	79.7	4	20	94	0	0	0	0	0
CLEARCUT	370	45.4	104	0	0	168	15	1	82	0
PASTURE	350	56.9	37	6	0	9	199	71	28	0
CROP	369	97.6	5	0	0	0	0	360	4	0
SOIL	1006	92.5	10	0	0	15	17	33	931	0
WATER	300	89.0	5	3	0	18	0	2	5	267
TOTAL	10557		1005	7024	149	221	355	486	1050	267

OVERALL PERFORMANCE = 9741/10,557 = 92.3%

AVERAGE PERFORMANCE BY COVER CLASS = 651.8/8 = 81.5%

Table 50. Statistical comparison among overall classification results for all three algorithms (L2, GML, SECHO) using the "best 4" channel subset (2,4,5,7) and based upon the 1979 supervised training statistics and sample block test data.

	Algorithm	and Table Location	% Correct	No. of Samples	Significant Differences[1]
Overall Classification Performance	L2	(Table 38)	81.8	10,557	All
	GML	(Table 39)	88.1		
	SECHO	(Table 40)	90.0		

[1] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

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Table 51. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using the "best 4" channel subset (2,4,5,7) and based upon the 1979 supervised training statistics and sample block test data.

Cover Class	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1/]
PINE	L2 GML SECHO	(Table 38) (Table 39) (Table 40)	85.5 91.0 92.9	775	L2/GML L2/SECHO
HDWD	L2 GML SECHO	Same as above	84.0 91.1 93.7	7269	All
TUPE	L2 GML SECHO	Same as above	55.1 58.5 57.6	118	None
CCUT	L2 GML SECHO	Same as above	68.6 60.5 58.5	370	L2/GML L2/SECHO
PAST	L2 GML SECHO	Same as above	70.9 82.6 83.1	350	L2/GML L2/SECHO
CROP	L2 GML SECHO	Same as above	88.1 79.7 81.6	369	L2/GML L2/SECHO
SOIL	L2 GML SECHO	Same as above	71.6 85.6 86.0	1006	L2/GML L2/SECHO
WATER	L2 GML SECHO	Same as above	85.7 78.7 79.7	300	L2/GML L2/SECHO

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 52. Statistical comparison among overall classification results for all three algorithms (L2, GML, SECHO) using all 7 channels and based upon the 1979 supervised training statistics and sample block test data.

	Algorithm and	Table Location	% Correct	No. of Samples	Significant Differences[1/]
Overall Classification Performance	L2	(Table 41)	85.3	10,557	All
	GML	(Table 42)	90.7		
	SECHO	(Table 43)	91.6		

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 53. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using all 7 channels and based upon the 1979 supervised training statistics and sample block test data.

Cover Class	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1]
PINE	L2 GML SECHO	(Table 41) (Table 42) (Table 43)	91.5 95.0 94.7	775	L2/GML L2/SECHO
HDWD	L2 GML SECHO	Same as above	88.2 93.2 94.8	7269	All
TUPE	L2 GML SECHO	Same as above	68.6 67.8 65.3	118	None
CCUT	L2 GML SECHO	Same as above	65.4 64.9 64.6	370	None
PAST	L2 GML SECHO	Same as above	70.3 83.4 84.6	350	L2/GML L2/SECHO
CROP	L2 GML SECHO	Same as above	87.8 81.0 81.0	369	L2/GML L2/SECHO
SOIL	L2 GML SECHO	Same as above	73.2 90.6 90.6	1006	L2/GML L2/SECHO
WATER	L2 GML SECHO	Same as above	87.3 90.7 91.6	300	L2/GML L2/SECHO

[1] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 54. Statistical comparison among overall classification results for all three algorithms (L2, GML, SECHO) using the "best 4" channel subset (1,3,4,6) and based upon the 1979 MCB training statistics and sample block test data.

	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1/]
Overall Classification Performance	L2	(Table 44)	77.4	10,557	All
	GML	(Table 45)	86.1		
	SECHO	(Table 46)	90.6		

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 55. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using the "best 4" channel subset (1,3,4,6) and based upon the 1979 MCB training statistics and sample block test data.

Cover Class	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1/]
PINE	L2 GML SECHO	(Table 44) (Table 45) (Table 46)	85.3 91.9 94.8	775	All
HDWD	L2 GML SECHO	Same as above	76.8 88.4 94.7	7269	All
TUPE	L2 GML SECHO	Same as above	47.5 62.7 40.7	118	L2/GML GML/SECHO
CCUT	L2 GML SECHO	Same as above	31.9 41.9 39.5	370	L2/GML L2/SECHO
PAST	L2 GML SECHO	Same as above	50.6 51.4 47.4	350	None
CROP	L2 GML SECHO	Same as above	97.0 99.2 98.6	369	L2/GML
SOIL	L2 GML SECHO	Same as above	93.9 91.3 94.7	1006	L2/GML GML/SECHO
WATER	L2 GML SECHO	Same as above	88.7 87.3 89.0	300	None

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 56. Statistical comparison among overall classification results for all three algorithms (L2, GML, SECHO) using all 7 channels and based upon the 1979 MCB training statistics and sample block test data.

	Algorithm and	Table Location	% Correct	No. of Samples	Significant Differences[1/]
Overall Classification Performance	L2	(Table 47)	81.4	10,557	All
	GML	(Table 48)	88.7		
	SECHO	(Table 49)	92.3		

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 57. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using all 7 channels and based upon the 1979 MCB training statistics and sample block test data.

Cover Class	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1/]
PINE	L2 GML SECHO	(Table 47) (Table 48) (Table 49)	89.3 93.3 94.6	775	L2/GML L2/SECHO
HDWD	L2 GML SECHO	Same as above	82.1 91.1 96.1	7269	All
TUPE	L2 GML SECHO	Same as above	58.5 83.9 79.7	118	L2/GML L2/SECHO
CCUT	L2 GML SECHO	Same as above	35.1 45.7 45.4	370	L2/GML L2/SECHO
PAST	L2 GML SECHO	Same as above	66.0 61.4 56.9	350	L2/SECHO
CROP	L2 GML SECHO	Same as above	98.6 98.6 97.6	369	None
SOIL	L2 GML SECHO	Same as above	87.1 90.8 92.5	1006	L2/GML L2/SECHO
WATER	L2 GML SECHO	Same as above	87.3 86.7 89.0	300	None

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 58. Classification Results Based Upon Supervised Training Statistics and the L-2 Minimum Distance Classifier, Using Channels 1, 2, 3, & 6 of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	66.2	260	121	9	3	0	0	0	0
HARDWOOD	6584	83.4	843	5489	73	115	14	7	43	0
TUPELO	145	22.8	0	97	33	15	0	0	0	0
REGEN. HDWD.	458	40.2	0	2	33	184	146	81	12	0
PASTURE	408	63.2	1	5	10	35	258	58	41	0
CROP	890	46.7	0	0	1	43	376	416	54	0
SOIL	439	73.3	0	0	1	0	115	1	322	0
WATER	350	90.3	19	8	3	0	1	0	3	316
TOTAL	9667		1123	5722	163	395	910	563	475	316

OVERALL PERFORMANCE = 7278/9667 = 75.3%

AVERAGE PERFORMANCE BY COVER CLASS = 486.1/8 = 60.8%

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Table 59. Classification Results Based Upon Supervised Training Statistics and the GML Classifier, Using Channels 1, 2, 3, & 6 of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	72.5	285	81	0	26	1	0	0	0
HARDWOOD	6584	90.8	275	5980	0	213	12	42	62	0
TUPELO	145	19.3	8	0	28	108	1	0	0	0
REGEN. HDWD.	458	55.0	0	0	0	252	83	81	42	0
PASTURE	408	48.5	4	0	0	29	198	109	68	0
CROP	890	73.6	0	0	0	47	125	655	63	0
SOIL	439	78.6	0	0	0	0	36	58	345	0
WATER	350	74.6	7	7	0	3	1	2	69	261
TOTAL	9667		579	6068	28	678	457	947	649	261

OVERALL PERFORMANCE = 8004/9667 = 82.8%

AVERAGE PERFORMANCE BY COVER CLASS = 512.9/8 = 64.1%

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Table 60. Classification Results Based Upon Supervised Training Statistics and the SECHO Classifier, Using Channels 1, 2, 3, & 6 of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	71.5	281	80	0	31	1	0	0	0
HARDWOOD	6584	92.8	165	6111	0	199	6	41	62	0
TUPELO	145	19.3	0	0	28	116	1	0	0	0
REGEN. HDWD.	458	72.9	0	0	0	334	41	51	32	0
PASTURE	408	40.4	3	0	0	35	165	146	59	0
CROP	890	88.0	0	0	0	40	38	783	29	0
SOIL	439	78.6	0	0	0	0	22	72	345	0
WATER	350	74.6	7	7	0	3	1	2	69	261
TOTAL	9667		456	6198	28	758	275	1095	596	261

OVERALL PERFORMANCE = 8308/9667 = 85.9%

AVERAGE PERFORMANCE BY COVER CLASS = 538.1/8 = 67.3%

Table 61. Classification Results Based Upon Supervised Training Statistics and the L-2 Minimum Distance Classifier, Using All 8 Channels of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	68.4	269	123	0	0	0	0	1	0
HARDWOOD	6584	81.1	877	5342	181	108	29	0	47	0
TUPELO	145	61.4	0	4	89	52	0	0	0	0
REGEN. HDWD.	458	17.7	4	3	27	81	305	2	36	0
PASTURE	408	81.4	0	1	4	33	332	24	14	0
CROP	890	80.8	0	0	0	15	131	719	25	0
SOIL	439	76.8	0	0	2	0	100	0	337	0
WATER	350	92.3	10	7	5	1	1	0	3	323
TOTAL	9667		1160	5480	308	290	898	745	463	323

OVERALL PERFORMANCE = 7492/9667 = 77.5%

AVERAGE PERFORMANCE BY COVER CLASS = 559.9/8 = 70.0%

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Table 62. Classification Results Based Upon Supervised Training Statistics and the GML Classifier, Using All 8 Channels of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	75.6	297	88	0	8	0	0	0	0
HARDWOOD	6584	92.8	139	6110	1	239	5	11	78	1
TUPELO	145	19.3	0	2	28	115	0	0	0	0
REGEN. HDWD.	458	81.4	1	2	0	373	63	3	16	0
PASTURE	408	50.0	2	0	0	81	204	60	61	0
CROP	890	98.3	0	0	0	0	1	875	14	0
SOIL	439	92.7	0	0	0	9	6	17	407	0
WATER	350	73.7	7	7	0	6	1	1	70	258
TOTAL	9667		446	6209	29	831	280	967	646	259

OVERALL PERFORMANCE = 8552/9667 = 88.5%

AVERAGE PERFORMANCE BY COVER CLASS = 583.8/8 = 73.0%

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Table 63. Classification Results Based Upon Supervised Training Statistics and the SECHO Classifier, Using All 8 Channels of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	75.1	295	91	0	7	0	0	0	0
HARDWOOD	6584	93.9	88	6180	1	222	3	11	78	1
TUPELO	145	19.3	0	2	28	115	0	0	0	0
REGEN. HDWD.	458	89.5	1	0	0	410	28	3	16	0
PASTURE	408	50.2	2	0	0	82	205	59	60	0
CROP	890	98.9	0	0	0	0	0	880	10	0
SOIL	439	92.7	0	0	0	9	6	17	407	0
WATER	350	73.7	7	7	0	6	1	1	70	258
TOTAL	9667		393	6280	29	851	243	971	641	259

OVERALL PERFORMANCE = 8663/9667 = 89.6%

AVERAGE PERFORMANCE BY COVER CLASS = 593.3/8 = 74.2%

Table 64. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the L-2 Minimum Distance Classifier, Using Channels 1, 3, 4, & 5 of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	79.4	312	81	0	0	0	0	0	0
HARDWOOD	6584	69.3	1751	4562	89	122	11	0	49	0
TUPELO	145	10.3	0	83	17	27	20	0	0	0
REGEN. HDWD.	458	43.7	27	110	64	200	24	0	31	2
PASTURE	408	69.6	0	20	1	18	284	30	55	0
CROP	890	57.8	0	0	1	1	366	514	8	0
SOIL	439	72.7	3	34	7	4	32	1	319	39
WATER	350	94.3	4	11	0	0	2	0	3	330
TOTAL	9667		2097	4901	179	372	739	545	465	371

OVERALL PERFORMANCE = 6536/9667 = 67.6%

AVERAGE PERFORMANCE BY COVER CLASS = 497.1/8 = 62.1%

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Table 65. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the GML Classifier, Using Channels 1, 3, 4, & 5 of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	82.2	323	66	0	0	0	0	0	4
HARDWOOD	6584	83.1	887	5472	15	121	5	1	60	23
TUPELO	145	17.9	0	106	26	1	12	0	0	0
REGEN. HDWD.	458	68.1	1	29	5	312	19	2	15	75
PASTURE	408	78.7	1	22	0	0	321	11	18	35
CROP	890	60.3	0	0	0	0	295	537	58	0
SOIL	439	86.3	1	8	0	1	16	0	379	34
WATER	350	94.9	7	7	0	0	2	0	2	332
TOTAL	9667		1220	5710	46	435	670	551	532	503

OVERALL PERFORMANCE = 7702/9667 = 79.7%

AVERAGE PERFORMANCE BY COVER CLASS = 571.5/8 = 71.4%

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Table 66. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the SECHO Classifier, Using Channels 1, 3, 4, & 5 of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	80.9	318	70	0	0	0	0	0	5
HARDWOOD	6584	90.9	445	5985	0	50	1	0	67	36
TUPELO	145	18.6	0	114	27	0	4	0	0	0
REGEN. HDWD.	458	69.2	0	27	0	317	7	0	12	95
PASTURE	408	78.9	1	22	0	0	322	4	19	40
CROP	890	59.4	0	0	0	0	303	529	56	2
SOIL	439	79.7	0	2	0	0	25	0	350	62
WATER	350	94.9	8	6	0	0	2	0	2	332
TOTAL	9667		772	6226	27	367	664	533	506	572

OVERALL PERFORMANCE = 8180/9667 = 84.6%

AVERAGE PERFORMANCE BY COVER CLASS = 572.5/8 = 71.6%

Table 67. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the L-2 Minimum Distance Classifier, Using All 8 Channels of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	76.6	301	92	0	0	0	0	0	0
HARDWOOD	6584	69.7	1779	4588	135	33	9	3	32	5
TUPELO	145	35.2	0	84	51	0	10	0	0	0
REGEN. HDWD.	458	58.3	0	47	14	267	19	1	98	12
PASTURE	408	72.1	0	9	0	19	294	7	79	0
CROP	890	72.6	0	0	0	1	230	646	13	0
SOIL	439	70.6	0	4	3	13	102	1	310	6
WATER	350	94.0	5	8	4	0	1	0	3	329
TOTAL	9667		2085	4832	207	333	665	658	535	352

OVERALL PERFORMANCE = 6786/9667 = 70.2%

AVERAGE PERFORMANCE BY COVER CLASS = 549.1/8 = 68.6%

Table 68. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the GML Classifier, Using All 8 Channels of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	82.7	325	64	0	0	0	0	0	4
HARDWOOD	6584	83.4	895	5491	6	102	5	0	49	36
TUPELO	145	20.0	0	105	29	0	11	0	0	0
REGEN. HDWD.	458	71.4	0	25	3	327	14	0	9	80
PASTURE	408	76.0	1	30	0	3	310	2	28	34
CROP	890	55.6	0	4	0	0	323	495	68	0
SOIL	439	92.9	0	0	0	4	10	0	408	17
WATER	350	94.3	8	9	0	0	1	0	2	330
TOTAL	9667		1229	5728	38	436	674	497	564	501

OVERALL PERFORMANCE = 7715/9667 = 79.8%

AVERAGE PERFORMANCE BY COVER CLASS = 576.3/8 = 72.0%

Table 69. Classification Results Based Upon Multi-Cluster Blocks Training Statistics and the SECHO Classifier, Using All 8 Channels of the 1980 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	RGHD	PAST	CROP	SOIL	WATR
PINE	393	83.7	329	62	0	0	0	0	0	2
HARDWOOD	6584	90.2	490	5939	2	64	1	0	47	41
TUPELO	145	19.3	0	113	28	0	4	0	0	0
REGEN. HDWD.	458	70.7	0	28	0	324	7	0	1	98
PASTURE	408	74.8	1	24	0	0	305	0	33	45
CROP	890	53.8	0	4	0	0	330	479	77	0
SOIL	439	93.4	0	0	0	2	9	0	410	18
WATER	350	94.3	8	9	0	0	1	0	2	330
TOTAL	9667		828	6179	30	390	657	479	570	534

OVERALL PERFORMANCE = 8144/9667 = 84.2%

AVERAGE PERFORMANCE BY COVER CLASS = 580.2/8 = 72.5%

Table 70. Statistical comparison among overall classification results for all 3 algorithms (L2, GML, SECHO) using the "best 4" channel subset (1,2,3,6) and based upon the 1980 supervised training statistics and sample block test data.

	Algorithm and	Table Location	% Correct	No. of Samples	Significant Differences[1]
Overall Classification Performance	L2	(Table 58)	75.3	9667	All
	GML	(Table 59)	82.8		
	SECHO	(Table 60)	85.9		

[1] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 71. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using the "best 4" channel subset (1,2,3,6) and based upon the 1980 supervised training statistics and sample block test data.

Cover Class	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1]
PINE	L2 GML SECHO	(Table 58) (Table 59) (Table 60)	66.2 72.5 71.5	393	None
HDWD	L2 GML SECHO	Same as above	83.4 90.8 92.8	6584	All
TUPE	L2 GML SECHO	Same as above	22.8 19.3 19.3	145	None
RGHD	L2 GML SECHO	Same as above	40.2 55.0 72.9	458	All
PAST	L2 GML SECHO	Same as above	63.2 48.5 40.4	408	All
CROP	L2 GML SECHO	Same as above	46.7 73.6 88.0	890	All
SOIL	L2 GML SECHO	Same as above	73.3 78.6 78.6	439	L2/GML L2/SECHO
WATER	L2 GML SECHO	Same as above	90.3 74.6 74.6	350	L2/GML L2/SECHO

1/ Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 72. Statistical comparison among overall classification results for all 3 algorithms (L2, GML, SECHO) using all 8 channels and based upon the 1980 supervised training statistics and sample block test data.

	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1/]
Overall Classification Performance	L2	(Table 61)	77.5	9667	All
	GML	(Table 62)	88.5		
	SECHO	(Table 63)	89.6		

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

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Table 73. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using all 8 channels and based upon the 1980 supervised training statistics and sample block test data.

Cover Class	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1/]
PINE	L2 GML SECHO	(Table 61) (Table 62) (Table 63)	68.4 75.6 75.1	393	L2/GML L2/SECHO
HDWD	L2 GML SECHO	Same as above	81.1 92.8 93.9	6584	All
TUPE	L2 GML SECHO	Same as above	61.4 19.3 19.3	145	L2/GML L2/SECHO
RGHD	L2 GML SECHO	Same as above	17.7 81.4 89.5	458	All
PAST	L2 GML SECHO	Same as above	81.4 50.0 50.2	408	L2/GML L2/SECHO
CROP	L2 GML SECHO	Same as above	80.8 98.3 98.9	890	L2/GML L2/SECHO
SOIL	L2 GML SECHO	Same as above	76.8 92.7 92.7	439	L2/GML L2/SECHO
WATER	L2 GML SECHO	Same as above	92.3 73.7 73.7	350	L2/GML L2/SECHO

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 74. Statistical comparison among overall classification results for all 3 algorithms (L2, GML, SECHO) using the "best 4" channel subset (1,3,4,5) and based upon the 1980 MCB training statistics and sample block test data.

	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1/]
Overall Classification Performance	L2	(Table 64)	67.6	9667	All
	GML	(Table 65)	79.7		
	SECHO	(Table 66)	84.6		

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 75. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using the "best 4" channel subset (1,3,4,5) and based upon the 1980 MCB training statistics and sample block test data.

Cover Class	Algorithm	Table Location	% Correct	No. of Samples	Significant Differences[1]
PINE	L2 GML SECHO	(Table 64) (Table 65) (Table 66)	79.4 82.2 80.9	393	None
HDWD	L2 GML SECHO	Same as above	69.3 83.1 90.9	6584	All
TUPE	L2 GML SECHO	Same as above	10.3 17.9 18.6	145	L2/GML L2/SECHO
RGHD	L2 GML SECHO	Same as above	43.7 68.1 69.1	458	L2/GML L2/SECHO
PAST	L2 GML SECHO	Same as above	69.6 78.7 78.9	408	L2/GML L2/SECHO
CROP	L2 GML SECHO	Same as above	57.8 60.3 59.4	890	None
SOIL	L2 GML SECHO	Same as above	72.7 86.3 79.7	439	All
WATER	L2 GML SECHO	Same as above	94.3 94.9 94.9	350	None

[1] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 76. Statistical comparison among overall classification results for all 3 algorithms (L2, GML, SECHO) using all 8 channels and based upon the 1980 MCB training statistics and sample block test data.

	Algorithm	and Table Location	% Correct	No. of Samples	Significant Differences[1/]
Overall Classification Performance	L2	(Table 67)	70.2	9667	All
	GML	(Table 68)	79.8		
	SECHO	(Table 69)	84.2		

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 77. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using all 8 channels and based upon the 1980 MCB training statistics and sample block test data.

Cover Class	Algorithm	Table and Location	% Correct	No. of Samples	Significant Differences[1/]
PINE	L2 GML SECHO	(Table 67) (Table 68) (Table 69)	76.6 82.7 83.7	393	L2/GML L2/SECHO
HDWD	L2 GML SECHO	Same as above	69.7 83.4 90.2	6584	All
TUPE	L2 GML SECHO	Same as above	35.2 20.0 19.3	145	L2/GML L2/SECHO
RGHD	L2 GML SECHO	Same as above	58.3 71.4 70.7	458	L2/GML L2/SECHO
PAST	L2 GML SECHO	Same as above	72.1 76.0 74.8	408	None
CROP	L2 GML SECHO	Same as above	72.6 55.6 53.8	890	L2/GML L2/SECHO
SOIL	L2 GML SECHO	Same as above	70.6 92.9 93.4	439	L2/GML L2/SECHO
WATER	L2 GML SECHO	Same as above	94.0 94.3 94.3	350	None

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

APPENDIX C (Tables 78-109)

Comparisons Between the 1979 Original TMS Data Set and the 1979 K-L Transformed TMS Data Set

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Table 78. Summary table of overall classification performances comparing the untransformed TMS and the K-L transformed data sets for all three classifiers.

Data Subset: "Best 3" Channels or 1st 3 Components

Classifier	Untransformed TMS[1/] (Channels 1,3,6)	Table Location	K-L Transformed Data (Components 1,2,3)	Table Location
L2	65.2[a]	(Table 80)	80.0%[b]	(Table 83)
GML	78.4[a]	(Table 81)	82.9[b]	(Table 84)
SECHO	86.8[a]	(Table 82)	86.6[a]	(Table 85)

Data Subset: "Best 4" Channels or 1st 4 Components

Classifier	Untransformed TMS[1/] (Channels 2,4,5,7)	Table Location	K-L Transformed Data (Components 1,2,3,4)	Table Location
L2	81.8[a]	(Table 86)	83.8[b]	(Table 89)
GML	88.1[b]	(Table 87)	84.6[a]	(Table 90)
SECHO	90.0[b]	(Table 88)	87.0[a]	(Table 91)

[1/] Significantly different overall classification performances between the untransformed and the K-L transformed data sets for each classifier is indicated by a different superscript (based upon a Newman-Keuls comparison with $\alpha = 0.10$).

Table 79. Summary table of overall class performances for three algorithms (L2, GML, SECHO) based upon four data sets.

Data Set Description	Overall Classification Performance (%) by Classifier (and Table Location)		
	L2[1/]	GML	SECHO
3 Channels (1,3,6), Untransformed	65.2[a] (Table 80)	78.4[b] (Table 81)	86.8[c] (Table 82)
1st 3 Components, K-L Transformed	80.0[a] (Table 83)	82.9[b] (Table 84)	86.6[c] (Table 85)
4 Channels (2,4,5,7), Untransformed	81.8[a] (Table 86)	88.1[b] (Table 87)	90.0[c] (Table 88)
1st 4 Components, K-L Transformed	83.8[a] (Table 89)	84.6[a] (Table 90)	87.0[b] (Table 91)

[1/] Different superscripts between columns of the same row indicate significantly different overall classification performances between classifiers (based upon a Newman-Keuls comparison with $\alpha = 0.10$).

Table 80. Classification Results Based Upon Supervised Training Statistics and the L2 Classifier, Using the Best Three Channels (1, 3, 6) of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	76.9	596	11	106	36	6	20	0	0
HARDWOOD	7269	69.1	1317	5022	831	82	4	13	0	0
TUPELO	118	45.8	18	0	54	46	0	0	0	0
CLEARCUT	370	49.5	64	0	2	183	82	21	15	3
PASTURE	350	43.4	69	0	33	92	152	4	0	0
CROP	369	27.6	0	0	20	181	66	102	0	0
SOIL	1006	50.4	0	0	1	478	17	3	507	0
WATER	300	88.3	2	2	0	26	0	1	4	265
TOTAL	10557		2066	5035	1047	1124	327	164	526	268

OVERALL PERFORMANCE = 6881/10,557 = 65.2%

AVERAGE PERFORMANCE BY COVER CLASS = 451/8 = 56.4%

Table 81. Waveband Evaluation Classification Results Using Channels 1, 3, & 6 (the best 3). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	94.7	734	5	6	22	1	6	0	1
HARDWOOD	7269	77.8	660	5658	731	100	70	[illegible]9	0	1
TUPELO	118	21.2	50	6	25	34	1	2	0	0
CLEARCUT	370	68.1	62	0	0	252	12	14	30	0
PASTURE	350	62.3	16	2	23	85	218	6	0	0
CROP	369	61.5	0	1	9	65	67	227	0	0
SOIL	1006	89.8	0	0	1	88	11	0	903	3
WATER	300	88.0	1	3	0	28	0	0	4	264
TOTAL	10557		1523	5675	795	674	380	304	937	269

OVERALL PERFORMANCE = 8281/10,557 = 78.4%

AVERAGE PERFORMANCE BY COVER CLASS = 563.4/8 = 70.4%

Table 82. Classification Results Based Upon Supervised Training Statistics and the SECHO Classifier, Using the Best Three Channels (1, 3, 6) of the 1979 TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	96.5	748	0	6	13	0	7	0	1
HARDWOOD	7269	89.1	272	6475	294	96	88	44	0	0
TUPELO	118	22.0	56	4	26	31	1	0	0	0
CLEARCUT	370	74.6	59	0	0	276	6	0	29	0
PASTURE	350	68.3	14	0	20	77	239	0	0	0
CROP	369	62.9	0	0	7	69	61	232	0	0
SOIL	1006	92.0	0	0	0	68	9	0	926	3
WATER	300	81.3	1	0	0	51	0	0	4	244
TOTAL	10557		1150	6479	353	681	404	137	959	248

OVERALL PERFORMANCE = 9166/10,557 = 86.8%

AVERAGE PERFORMANCE BY COVER CLASS = 586.7/8 = 73.3%

Table 83. Classification Results Based Upon Supervised Training Statistics and the L-2 Minimum Euclidean Distance Classifier, Using the 1st 3 Components of the 1979 Principal Component TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	89.0	690	9	1	59	4	12	0	0
HARDWOOD	7269	80.9	371	5880	334	60	80	544	0	0
TUPELO	118	50.8	7	5	60	0	0	46	0	0
CLEARCUT	370	61.1	86	0	2	226	11	2	39	4
PASTURE	350	69.4	3	2	1	30	243	71	0	0
CROP	369	89.7	0	2	1	1	34	331	0	0
SOIL	1006	75.2	2	0	3	204	39	0	757	1
WATER	300	87.0	5	1	2	24	0	3	4	261
TOTAL	10557		1164	5899	404	604	411	1009	800	266

OVERALL PERFORMANCE = 8448/10,557 = 80.0%

AVERAGE PERFORMANCE BY COVER CLASS = 603.1/8 = 75.4%

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Table 84. Classification Results Based Upon Supervised Training Statistics and the GML Classifier, Using the 1st 3 Components of the 1979 Principal Component TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	90.1	698	0	1	59	16	1	0	0
HARDWOOD	7269	85.9	336	6244	264	218	63	144	0	0
TUPELO	118	45.8	0	3	54	10	1	50	0	0
CLEARCUT	370	47.8	66	0	0	177	58	1	61	7
PASTURE	350	80.0	6	3	1	42	280	18	0	0
CROP	369	87.0	0	4	0	2	42	221	0	0
SOIL	1006	74.3	0	0	0	246	12	1	747	0
WATER	300	76.3	0	2	1	56	2	2	8	229
TOTAL	10557		1106	6256	321	810	474	538	816	236

OVERALL PERFORMANCE = 8750/10,557 = 82.9%

AVERAGE PERFORMANCE BY COVER CLASS = 587.2/8 = 73.4%

Table 85. Classification Results Based Upon Supervised Training Statistics and the SECHO Classifier, Using the 1st 3 Components of the 1979 Principal Component TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	91.2	707	2	0	63	3	0	0	0
HARDWOOD	7269	91.3	120	6634	141	202	110	61	0	1
TUPELO	118	52.5	3	7	62	3	1	42	0	0
CLEARCUT	370	50.8	58	0	0	188	56	0	68	0
PASTURE	350	84.9	0	2	0	43	297	8	0	0
CROP	369	87.3	0	1	5	2	39	322	0	0
SOIL	1006	70.6	0	0	0	262	33	1	710	0
WATER	300	73.0	0	2	1	66	2	2	8	219
TOTAL	10557		888	6648	209	829	541	436	786	220

OVERALL PERFORMANCE = 9139/10,557 = 86.6%

AVERAGE PERFORMANCE BY COVER CLASS = 601.6/8 = 75.2%

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Table 86. Classification Results Using Channels 2, 4, 5, & 7 (the best 4). (1979 TMS Data, Supervised Training Statistics, L2 Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	85.5	663	8	2	85	6	8	3	0
HARDWOOD	7269	84.0	331	6103	347	72	66	350	0	0
TUPELO	118	55.1	7	16	65	0	0	30	0	0
CLEARCUT	370	68.6	59	0	7	254	9	1	37	3
PASTURE	350	70.9	3	3	1	29	248	66	0	0
CROP	369	88.1	0	10	1	1	32	325	0	0
SOIL	1006	71.6	12	0	5	195	71	3	720	0
WATER	300	85.7	7	0	3	23	0	3	7	257
TOTAL	10557		1082	6140	431	659	432	786	767	260

OVERALL PERFORMANCE = 10,557/8635 = 81.8%

AVERAGE PERFORMANCE BY COVER CLASS = 609.5/8 = 76.2%

Table 87. Classification Results Using Channels 2, 4, 5, & 7 (the best 4). (1979 TMS Data, Supervised Training Statistics, GML Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	91.0	705	4	0	40	26	0	0	0
HARDWOOD	7269	91.1	114	6621	140	320	62	12	0	0
TUPELO	118	58.5	0	4	69	7	5	32	0	1
CLEARCUT	370	60.5	48	0	0	224	49	0	49	0
PASTURE	350	82.6	0	2	1	38	289	20	0	0
CROP	369	79.7	0	1	8	2	64	294	0	0
SOIL	1006	85.6	0	0	0	123	19	0	861	3
WATER	300	78.7	0	3	2	55	1	0	3	236
TOTAL	10557		867	6635	220	809	515	358	913	240

OVERALL PERFORMANCE = 9299/10,557 = 88.1%

AVERAGE PERFORMANCE BY COVER CLASS = 627.7/8 = 78.5%

Table 88. Classification Results Using Channels 2, 4, 5, & 7 (the best 4). (1979 TMS Data, Supervised Training Statistics, SECHO Classifier)

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	92.9	720	1	0	18	36	0	0	0
HARDWOOD	7269	93.7	73	6811	45	248	87	4	0	1
TUPELO	118	57.6	0	9	68	6	4	30	0	1
CLEARCUT	370	58.9	41	0	0	218	65	0	46	0
PASTURE	350	83.1	0	2	0	41	291	16	0	0
CROP	369	81.6	0	0	8	2	58	301	0	0
SOIL	1006	86.0	0	0	0	119	19	0	865	3
WATER	300	75.0	0	3	2	66	1	0	3	225
TOTAL	10557		834	6826	123	718	561	351	914	230

OVERALL PERFORMANCE = 9499/10,557 = 90.0%

AVERAGE PERFORMANCE BY COVER CLASS = 628.8/8 = 78.6%

Table 89. Classification Results Based Upon Supervised Training Statistics and the L2 Classifier, Using the 1st 4 Components of the 1979 Principal Component TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	89.2	691	9	2	60	4	9	0	0
HARDWOOD	7269	86.1	374	6260	301	73	63	198	0	0
TUPELO	118	63.6	7	11	75	0	0	25	0	0
CLEARCUT	370	61.6	87	0	3	228	11	1	37	3
PASTURE	350	68.6	3	2	2	37	240	66	0	0
CROP	369	89.4	0	1	1	1	36	330	0	0
SOIL	1006	75.5	2	0	2	203	38	0	760	1
WATER	300	87.0	6	1	2	23	0	3	4	261
TOTAL	10557		1170	6284	388	625	392	632	801	265

OVERALL PERFORMANCE = 8845/10,557 = 83.8%

AVERAGE PERFORMANCE BY COVER CLASS = 621/8 = 77.6%

Table 90. Classification Results Based Upon Supervised Training Statistics and the GML Classifier, Using the 1st 4 Components of the 1979 Principal Component TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	92.0	713	3	2	35	22	0	0	0
HARDWOOD	7269	88.7	337	6450	188	250	37	6	0	1
TUPELO	118	36.4	0	22	43	12	20	21	0	0
CLEARCUT	370	55.9	56	0	0	207	41	0	66	0
PASTURE	350	86.3	0	2	0	31	302	15	0	0
CROP	369	73.2	0	0	10	0	89	270	0	0
SOIL	1006	69.9	0	0	0	276	27	0	703	0
WATER	300	81.0	0	4	0	45	2	0	6	243
TOTAL	10557		1106	6481	243	856	540	312	775	244

OVERALL PERFORMANCE = 8931/10,557 = 84.6%

AVERAGE PERFORMANCE BY COVER CLASS = 583.4/8 = 72.9%

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Table 91. Classification Results Based Upon Supervised Training Statistics and the SECHO Classifier, Using the 1st 4 Components of the 1979 Principal Component TMS Data.

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATR
PINE	775	92.9	720	2	2	29	22	0	0	0
HARDWOOD	7269	92.4	154	6714	118	224	53	4	0	2
TUPELO	118	28.8	5	34	34	5	22	18	0	0
CLEARCUT	370	56.2	50	0	0	208	40	0	72	0
PASTURE	350	85.7	0	1	0	34	300	15	0	0
CROP	369	71.8	0	0	10	0	94	265	0	0
SOIL	1006	69.7	0	0	0	280	25	0	701	0
WATER	300	81.0	0	4	0	45	2	0	6	243
TOTAL	10557		929	6755	164	825	558	302	779	245

OVERALL PERFORMANCE = 9185/10,557 = 87.0%

AVERAGE PERFORMANCE BY COVER CLASS = 578.5/8 = 72.3%

Table 92. Statistical comparison among overall classification results for all 3 algorithms (L2, GML, SECHO) using the first 3 components of the 1979 K-L transformed TMS data and based upon the 1979 supervised statistics and sample block test data.

	Algorithm	Table Location	% Correct	No. of Samples	Significant Differences[1/]
Overall Classification Performance	L2	(Table 83)	80.0	10,557	All
	GML	(Table 84)	82.9		
	SECHO	(Table 85)	86.6		

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 93. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using the first 3 components of the 1979 K-L transformed TMS data and based upon the 1979 supervised training statistics and sample block test data.

Cover Class	Algorithm	Table Location	% Correct	No. of Samples	Significant Differences[1/]
PINE	L2 GML SECHO	(Table 83) (Table 84) (Table 85)	89.0 90.1 91.2	775	None
HDWD	L2 GML SECHO	Same as above	80.9 85.9 91.3	7269	All
TUPE	L2 GML SECHO	Same as above	50.8 45.8 52.5	118	None
CCUT	L2 GML SECHO	Same as above	61.1 47.8 50.8	370	GML/L2 SECHO/L2
PAST	L2 GML SECHO	Same as above	69.4 80.0 84.9	350	All
CROP	L2 GML SECHO	Same as above	89.7 87.0 87.3	369	None
SOIL	L2 GML SECHO	Same as above	75.2 74.3 70.6	1006	SECHO/GML SECHO/L2
WATER	L2 GML SECHO	Same as above	87.0 76.3 73.0	300	SECHO/L2 GML/L2

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 94. Statistical comparison between overall classification results for the L2 classifier for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best 3 channel feature set based upon 1979 supervised training statistics and sample block test data.

	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
Overall Classification Performance	Feature Selection (Untransformed)	(Table 80)	65.2	10,557	Yes
	K-L Transformed	(Table 83)	80.0		

[1] Feature selection optimum subset includes channels 1, 3, & 6 of the original 1979 TMS data set.

K-L transformation includes the first 3 components of the K-L transformed 1979 data set.

[2] Classification performance difference is based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 95. Statistical comparison between classification results for the L2 classifier by cover class for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best three channel feature set based upon 1979 supervised training statistics and sample block test data.

Cover Class	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
PINE	Feature Selection (Untransformed)	(Table 80)	76.9	775	Yes
	K-L Transformed	(Table 83)	89.0		
HDWD	Feature Selection (Untransformed)	Same as above	69.1	7269	Yes
	K-L Transformed		80.9		
TUPE	Feature Selection (Untransformed)	Same as above	45.8	118	No
	K-L Transformed		50.8		
CCUT	Feature Selection (Untransformed)	Same as above	49.5	370	Yes
	K-L Transformed		61.1		
PAST	Feature Selection (Untransformed)	Same as above	43.4	350	Yes
	K-L Transformed		69.4		
CROP	Feature Selection (Untransformed)	Same as above	27.6	369	Yes
	K-L Transformed		89.7		
SOIL	Feature Selection (Untransformed)	Same as above	50.4	1006	Yes
	K-L Transformed		75.2		
WATER	Feature Selection (Untransformed)	Same as above	88.3	300	No
	K-L Transformed		87.0		

1/ Feature selection optimum subset includes channels 1, 3, & 6 of the original 1979 TMS data set.

K-L transformation includes the first 3 components of the K-L transformed 1979 data set.

2/ Classification performance differences are based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 96. Statistical comparison between overall classification results for the GML classifier for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best 3 channel feature set based upon 1979 supervised training statistics and sample block test data.

	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
Overall Classification Performance	Feature Selection (Untransformed)	(Table 81)	78.4	10,557	Yes
	K-L Transformed	(Table 84)	82.9		

[1] Feature selection optimum subset includes channels 1, 3, & 6 of the original 1979 TMS data set.

K-L transformation includes the first 3 components of the K-L transformed 1979 data set.

[2] Classification performance difference is based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 97. Statistical comparison between classification results for the GML classifier by cover class for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best three channel feature set based upon 1979 supervised training statistics and sample block test data.

Cover Class	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
PINE	Feature Selection (Untransformed)	(Table 81)	94.7	775	Yes
	K-L Transformed	(Table 84)	90.1		
HDWD	Feature Selection (Untransformed)	Same as above	77.8	7269	Yes
	K-L Transformed		85.9		
TUPE	Feature Selection (Untransformed)	Same as above	21.2	118	Yes
	K-L Transformed		45.8		
CCUT	Feature Selection (Untransformed)	Same as above	68.1	370	Yes
	K-L Transformed		47.8		
PAST	Feature Selection (Untransformed)	Same as above	62.3	350	Yes
	K-L Transformed		80.0		
CROP	Feature Selection (Untransformed)	Same as above	61.5	369	Yes
	K-L Transformed		87.0		
SOIL	Feature Selection (Untransformed)	Same as above	89.8	1006	Yes
	K-L Transformed		74.3		
WATER	Feature Selection (Untransformed)	Same as above	88.0	300	Yes
	K-L Transformed		76.3		

1/ Feature selection optimum subset includes channels 1, 3, & 6 of the original 1979 TMS data set.

K-L transformation includes the first 3 components of the K-L transformed 1979 data set.

2/ Classification performance differences are based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 98. Statistical comparison between overall classification results for the SECHO classifier for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best 3 channel feature set based upon 1979 supervised training statistics and sample block test data.

	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
Overall Classification Performance	Feature Selection (Untransformed)	(Table 82)	86.8	10,557	[illegible]
	K-L Transformed	(Table 85)	86.6		

[1] Feature selection optimum subset includes channels 1, 3, & 6 of the original 1979 TMS data set.

K-L transformation includes the first 3 components of the K-L transformed 1979 data set.

[2] Classification performance difference is based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 99. Statistical comparison between classification results for the SECHO classifier by cover class for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best three channel feature set based upon the 1979 supervised training statistics and sample block test data.

Cover Class	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
PINE	Feature Selection (Untransformed)	(Table 82)	96.5	775	No
	K-L Transformed	(Table 85)	91.2		
HDWD	Feature Selection (Untransformed)	Same as above	89.1	7269	Yes
	K-L Transformed		91.3		
TUPE	Feature Selection (Untransformed)	Same as above	22.0	118	Yes
	K-L Transformed		52.5		
OCUT	Feature Selection (Untransformed)	Same as above	74.6	370	Yes
	K-L Transformed		50.8		
PAST	Feature Selection (Untransformed)	Same as above	68.3	350	Yes
	K-L Transformed		84.9		
CROP	Feature Selection (Untransformed)	Same as above	62.9	369	Yes
	K-L Transformed		87.3		
SOIL	Feature Selection (Untransformed)	Same as above	92.0	1006	Yes
	K-L Transformed		70.6		
WATER	Feature Selection (Untransformed)	Same as above	81.3	300	Yes
	K-L Transformed		73.0		

[1] Feature selection optimum subset includes channels 1, 3, & 6 of the original 1979 TMS data set.

K-L transformation includes the first 3 components of the K-L transformed 1979 data set.

[2] Classification performance differences are based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 100. Statistical comparison among overall classification results for all 3 algorithms (L2, GML, SECHO) using the first 4 components of the 1979 K-L transformed TMS data and based upon the 1979 supervised statistics and sample block test data.

	Algorithm	Table Location	% Correct	No. of Samples	Significant Differences[1/]
Overall Classification Performance	L2	(Table 89)	83.8	10,557	L2/SECHO
	GML	(Table 90)	84.6		GML/SECHO
	SECHO	(Table 91)	87.0		

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 101. Statistical comparison among classification results by cover class for all three algorithms (L2, GML, SECHO) using the 1st 4 components of the 1979 K-L transformed TMS data and based upon the 1979 supervised training statistics and sample block test data.

Cover Class	Algorithm	Table Location	% Correct	No. of Samples	Significant Differences[1/]
PINE	L2 GML SECHO	(Table 89) (Table 90) (Table 91)	89.2 92.0 92.9	775	L2/GML L2/SECHO
HDWD	L2 GML SECHO	Same as above	86.1 88.7 92.4	7269	All
TUPE	L2 GML SECHO	Same as above	63.6 36.4 28.8	118	SECHO/L2 GML/L2
CCUT	L2 GML SECHO	Same as above	61.6 55.9 56.2	370	None
PAST	L2 GML SECHO	Same as above	68.6 86.3 85.7	350	L2/SECHO L2/GML
CROP	L2 GML SECHO	Same as above	89.4 73.2 71.8	369	SECHO/L2 GML/L2
SOIL	L2 GML SECHO	Same as above	75.5 69.9 69.7	1006	SECHO/L2 GML/L2
WATER	L2 GML SECHO	Same as above	87.0 81.0 81.0	300	SECHO/L2 GML/L2

[1/] Classification algorithms which are significantly different are indicated based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 102. Statistical comparison between overall classification results for the L2 classifier for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best 4 channel feature set based upon 1979 supervised training statistics and sample block test data.

	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
Overall Classification Performance	Feature Selection (Untransformed)	(Table 86)	81.8	10,557	Yes
	K-L Transformed	(Table 89)	83.8		

[1] Feature selection optimum subset includes channels 2, 4, 5, & 7 of the original 1979 TMS data set.

K-L transformation includes the first 4 components of the K-L transformed 1979 data set.

[2] Classification performance difference is based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 103. Statistical comparison between classification results for the L2 classifier by cover class for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best four channel feature set based upon 1979 supervised training statistics and sample block test data.

Cover Class	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
PINE	Feature Selection (Untransformed)	(Table 86)	85.5	775	Yes
	K-L Transformed	(Table 89)	89.2		
HDWD	Feature Selection (Untransformed)	Same as above	84.0	7269	Yes
	K-L Transformed		86.1		
TUPE	Feature Selection (Untransformed)	Same as above	55.1	118	No
	K-L Transformed		63.6		
CCUT	Feature Selection (Untransformed)	Same as above	68.6	370	Yes
	K-L Transformed		61.6		
PAST	Feature Selection (Untransformed)	Same as above	70.9	350	No
	K-L Transformed		68.6		
CROP	Feature Selection (Untransformed)	Same as above	88.1	369	No
	K-L Transformed		89.4		
SOIL	Feature Selection (Untransformed)	Same as above	71.6	1006	Yes
	K-L Transformed		75.5		
WATER	Feature Selection (Untransformed)	Same as above	85.7	300	No
	K-L Transformed		87.0		

[1] Feature selection optimum subset includes channels 2, 4, 5, & 7 of the original 1979 TMS data set.

K-L transformation includes the first 4 components of the K-L transformed 1979 data set.

[2] Classification performance differences are based upon a Newman-Keuls comparison with $\alpha = 0.10$.

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Table 104. Statistical comparison between overall classification results for the GML classifier for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best 4 channel feature set based upon 1979 supervised training statistics and sample block test data.

	Reduction Technique 1/	Table Location	% Correct	No. of Samples	Significant Difference? 2/
Overall Classification Performance	Feature Selection (Untransformed)	(Table 87)	88.1	10,557	Yes
	K-L Transformed	(Table 90)	84.6		

1/ Feature selection optimum subset includes channels 2, 4, 5, & 7 of the original 1979 TMS data set.

K-L transformation includes the first 4 components of the K-L transformed 1979 data set.

2/ Classification performance difference is based upon a Newman-Keuls comparison with $\alpha = 0.10$.

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Table 105. Statistical comparison between classification results for the GML classifier by cover class for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best four channel feature set based upon 1979 supervised training statistics and sample block test data.

Cover Class	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
PINE	Feature Selection (Untransformed)	(Table 87)	91.0	775	No
	K-L Transformed	(Table 90)	92.0		
HDWD	Feature Selection (Untransformed)	Same as above	91.1	7269	Yes
	K-L Transformed		88.7		
TUPE	Feature Selection (Untransformed)	Same as above	58.5	118	Yes
	K-L Transformed		36.4		
CCUT	Feature Selection (Untransformed)	Same as above	60.5	370	No
	K-L Transformed		55.9		
PAST	Feature Selection (Untransformed)	Same as above	82.6	350	No
	K-L Transformed		86.3		
CROP	Feature Selection (Untransformed)	Same as above	79.7	369	Yes
	K-L Transformed		73.2		
SOIL	Feature Selection (Untransformed)	Same as above	85.6	1006	Yes
	K-L Transformed		69.9		
WATER	Feature Selection (Untransformed)	Same as above	78.7	300	No
	K-L Transformed		81.0		

[1] Feature selection optimum subset includes channels 2, 4, 5, & 7 of the original 1979 TMS data set.

K-L transformation includes the first 4 components of the K-L transformed 1979 data set.

[2] Classification performance differences are based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 106. Statistical comparison between overall classification results for the SECHO classifier for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best 4 channel feature set based upon 1979 supervised training statistics and sample block test data.

	Reduction Technique[1/]	Table Location	% Correct	No. of Samples	Significant Difference?[2/]
Overall Classification Performance	Feature Selection (Untransformed)	(Table 88)	90.0	10,557	Yes
	K-L Transformed	(Table 91)	87.0		

[1/] Feature selection optimum subset includes channels 2, 4, 5, & 7 of the original 1979 TMS data set.

K-L transformation includes the first 4 components of the K-L transformed 1979 data set.

[2/] Classification performance difference is based upon a Newman-Keuls comparison with $\alpha = 0.10$.

Table 107. Statistical comparison between classification results for the SECHO classifier by cover class for two dimensionality reduction techniques (Feature Selection, K-L transformation) for the best four channel feature set based upon 1979 supervised training statistics and sample block test data.

Cover Class	Reduction Technique[1]	Table Location	% Correct	No. of Samples	Significant Difference?[2]
PINE	Feature Selection (Untransformed)	(Table 88)	92.9	775	No
	K-L Transformed	(Table 91)	92.9		
HDWD	Feature Selection (Untransformed)	Same as above	93.7	7269	Yes
	K-L Transformed		92.4		
TUPE	Feature Selection (Untransformed)	Same as above	57.6	118	Yes
	K-L Transformed		28.8		
CCUT	Feature Selection (Untransformed)	Same as above	58.9	370	No
	K-L Transformed		56.2		
PAST	Feature Selection (Untransformed)	Same as above	83.1	350	No
	K-L Transformed		85.7		
CROP	Feature Selection (Untransformed)	Same as above	81.6	369	Yes
	K-L Transformed		71.8		
SOIL	Feature Selection (Untransformed)	Same as above	86.0	1006	Yes
	K-L Transformed		69.7		
WATER	Feature Selection (Untransformed)	Same as above	79.7	300	No
	K-L Transformed		81.0		

1/ Feature selection optimum subset includes channels 2, 4, 5, & 7 of the original 1979 TMS data set.

K-L transformation includes the first 4 components of the K-L transformed 1979 data set.

2/ Classification performance differences are based upon a Newman-Keuls comparison with $\alpha = 0.10$.

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Table 108. Statistics from original 1979 TMS data (sampled every 5th line and 5th column) used in calculation of K-L transformation matrix.

	Channel 1	2	3	4	5	6	7
Mean Vector	59.8	61.4	44.8	128.9	113.4	59.9	78.1
Standard Deviation	12.0	18.2	23.2	29.5	24.5	24.4	30.6
Covariance Matrix Diagonal	144.6	330.9	538.6	868.6	600.5	596.7	935.1

Total Variance = 4014.90

Correlation Matrix

1.00						
0.95	1.00					
0.90	0.96	1.00				
-0.02	0.01	-0.07	1.00			
0.16	0.21	0.19	0.91	1.00		
0.67	0.74	0.82	0.26	0.58	1.00	
0.33	0.43	0.55	-0.10	0.25	0.73	1.00

Covariance Matrix

144.6						
208.5	330.9					
252.3	404.8	538.6				
-5.9	3.7	-51.2	868.6			
46.0	94.9	106.5	657.5	600.5		
195.4	330.0	463.7	184.1	349.2	596.7	
122.8	238.8	388.7	-87.8	185.7	543.2	935.1

Table 109. Summary of 1979 K-L Transformed TMS Data.

Matrix of Eigenvectors

	CH 1	CH 2	CH 3	CH 4	CH 5	CH 6	CH 7
(λ_1) Eigenvector 1	0.18140	-0.09369	-0.32157	-0.26026	0.69161	-0.29629	-0.47017
(λ_2) Eigenvector 2	0.30786	-0.14271	-0.43681	-0.36567	0.14429	0.30636	0.66758
(λ_3) Eigenvector 3	0.41710	-0.23906	-0.43389	-0.02481	-0.62199	0.6217	-0.43505
(λ_4) Eigenvector 4	0.21030	0.75156	-0.04241	-0.34249	-0.22526	-0.45783	0.10712
(λ_5) Eigenvector 5	0.33933	0.50853	0.09323	0.16958	0.20906	0.69222	-0.25674
(λ_6) Eigenvector 6	0.52169	-0.02982	-0.03139	0.71851	0.13918	-0.35212	0.25758
(λ_7) Eigenvector 7	0.51653	-0.29895	0.71137	-0.36826	-0.01282	-0.04145	-0.01657

	Eigenvalue	Percent of Variance	Cumulative Percent	MSE
λ_1	2069.27	51.54%	51.54%	48.46
λ_2	1357.44	33.81	85.35	14.65
λ_3	501.46	12.49	97.84	2.16
λ_4	58.19	1.45	99.29	0.71
λ_5	14.06	0.35	99.64	0.36
λ_6	8.72	0.22	99.86	0.14
λ_7	5.77	0.14	100.0	0.00

APPENDIX D (Tables 110-118)

1980 SAR and MSS Classification Results
Used in the Quantitative Evaluation of the SAR Data
and in the SAR/MSS Comparison

Table 110. Classification Results for the 15 m SAR Data Using the GML Per-Point Classifier.

TEST CLASS PERFORMANCE

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	NUMBER OF SAMPLES CLASSIFIED INTO						
			PINE	HDWD	RGHD	PAST	CROP	SOIL	WATR
PINE	840	45.7	384	9	29	180	88	126	24
HARDWOOD	3131	37.2	139	1166	1119	51	559	97	0
REGEN. HDWD.	1490	28.3	281	134	421	71	370	207	6
PASTURE	1239	25.1	525	39	84	311	132	145	3
CROP	2250	19.9	412	83	215	43	447	1004	46
SOIL	1398	50.1	93	0	0	0	7	700	598
WATER	552	83.9	16	0	0	0	0	73	463
TOTAL	10900		1850	1431	1868	656	1603	2352	1140

OVERALL PERFORMANCE (3892/10900) = 35.7%

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Table 111. Classification Results for the 15 m SAR Data Using the Per-Field Classifier.

TEST CLASS PERFORMANCE

COVER CLASS	NO. OF FIELDS	% FIELD CORRECT	NO. OF SAMPLES	% SAMPLE CORRECT	NUMBER OF FIELDS CLASSIFIED AS: PINE	HDWD	RGHD	PAST	CROP	SOIL	WATR
PINE	10	60.0	840	37.4	6	0	0	3	1	0	0
HARDWOOD	11	81.8	3131	93.6	0	9	2	0	0	0	0
REGEN. HDWD.	13	46.2	1490	70.1	2	2	6	0	2	1	0
PASTURE	8	50.0	1239	48.8	4	0	0	4	0	0	0
CROP	19	21.1	2250	35.3	1	1	3	0	4	10	0
SOIL	8	87.5	1398	93.6	0	0	0	0	0	7	1
WATER	15	86.7	552	82.6	0	0	0	0	0	2	13
TOTAL	84		10900		13	12	11	7	7	20	14

OVERALL SAMPLE PERFORMANCE (7455/10900) = 68.4%

OVERALL FIELD PERFORMANCE (49/84) = 58.3%

Table 112. Classification Results for the 15 m SAR Data Using the SECHO Classifier.

TEST CLASS PERFORMANCE

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	NUMBER OF SAMPLES CLASSIFIED INTO						
			PINE	HDWD	RGHD	PAST	CROP	SOIL	WATR
PINE	840	52.9	444	8	60	218	64	46	0
HARDWOOD	3131	99.4	0	3113	0	0	18	0	0
REGEN. HDWD.	1490	57.9	81	199	862	0	251	97	0
PASTURE	1239	16.0	808	32	141	198	60	0	0
CROP	2250	33.4	58	185	203	0	752	1052	0
SOIL	1398	94.1	49	5	0	0	17	1315	12
WATER	552	58.0	37	27	8	5	37	118	320
TOTAL	10900		1477	3569	1274	421	1199	2628	332

OVERALL PERFORMANCE (7004/10900) = 64.3%

Table 113. Classification Results for the 30 m SAR Data Using the GML Per-Point Classifier.

TEST CLASS PERFORMANCE

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	NUMBER OF SAMPLES CLASSIFIED INTO						
			PINE	HDWD	RGHD	PAST	CROP	SOIL	WATR
PINE	249	65.5	163	0	4	44	19	15	4
HARDWOOD	840	52.6	4	442	327	3	62	2	0
REGEN. HDWD.	442	45.0	65	33	199	8	97	40	0
PASTURE	360	19.7	219	3	20	71	36	11	0
CROP	690	25.8	76	30	93	1	178	304	8
SOIL	414	71.0	31	0	1	0	3	294	85
WATER	161	62.7	2	1	1	0	4	52	101
TOTAL	3156		560	509	645	127	399	718	198

OVERALL PERFORMANCE (1448/3156) = 45.9%

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Table 114. Classification Results for the 30 m SAR Data Using the Per-Field Classifier.

TEST CLASS PERFORMANCE

COVER CLASS	NO. OF FIELDS	% FIELD CORRECT	NO. OF SAMPLES	% SAMPLE CORRECT	NUMBER OF FIELDS CLASSIFIED AS PINE	HDWD	RGHD	PAST	CROP	SOIL	WATR	NOT CLSD
PINE	10	80.0	249	90.4	8	0	0	1	1	0	0	0
HARDWOOD	11	81.8	840	93.3	0	9	2	0	0	0	0	0
REGEN. HDWD.	13	46.2	442	66.1	2	2	6	0	1	2	0	0
PASTURE	8	37.5	360	41.9	5	0	0	3	0	0	0	0
CROP	19	21.1	690	34.6	1	1	3	0	4	9	1	0
SOIL	8	12.5	414	46.4	1	0	0	0	0	1	6	0
WATER	15	53.3	161	70.8	0	0	0	0	1	4	8	2
TOTAL	84		3156		17	12	11	4	7	16	15	2

OVERALL SAMPLE PERFORMANCE (1998/3156) = 63.3%

OVERALL FIELD PERFORMANCE (39/84) = 46.4%

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Table 115. Classification Results for the 30 m SAR Data Using the SECHO Classifier.

TEST CLASS PERFORMANCE

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	NUMBER OF SAMPLES CLASSIFIED INTO						
			PINE	HDWD	RGHD	PAST	CROP	SOIL	WATR
PINE	249	53.8	134	3	11	73	20	8	0
HARDWOOD	840	97.9	0	822	16	0	2	0	0
REGEN. HDWD.	442	63.6	48	47	281	4	37	25	0
PASTURE	360	43.6	155	7	34	157	6	1	0
CROP	690	50.9	0	62	82	0	351	185	10
SOIL	414	65.0	31	2	1	2	23	269	86
WATER	161	39.8	7	15	4	0	44	27	64
TOTAL	3156		375	958	429	236	483	515	160

OVERALL PERFORMANCE (2078/3156) = 65.8%

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Table 116. Classification Results for the 30 m MSS Data Using the GML Per-Point Classifier.

TEST CLASS PERFORMANCE

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	NUMBER OF SAMPLES CLASSIFIED INTO						
			PINE	HDWD	RGHD	PAST	CROP	SOIL	WATR
PINE	134	75.4	101	23	0	0	0	0	10
HARDWOOD	1495	91.2	52	1364	63	0	0	0	16
REGEN. HDWD.	577	86.7	0	4	500	6	6	54	7
PASTURE	271	87.1	0	0	26	236	1	4	4
CROP	575	95.3	0	0	20	6	548	1	0
SOIL	291	99.3	0	0	0	0	1	289	1
WATER	193	94.8	7	0	1	0	0	2	183
TOTAL	3536		160	1391	610	248	556	350	221

OVERALL PERFORMANCE (3221/3536) = 91.1%

Table 117. Classification Results for the 30 m MSS Data Using the Per-Field Classifier.

TEST CLASS PERFORMANCE

COVER CLASS	NO. OF FIELDS	% FIELD CORRECT	NO. OF SAMPLES	% SAMPLE CORRECT	NUMBER OF FIELDS CLASSIFIED AS						
					PINE	HDWD	RGHD	PAST	CROP	SOIL	WATR
PINE	5	80.0	134	73.9	4	1	0	0	0	0	0
HARDWOOD	8	100.0	1495	100.0	0	8	0	0	0	0	0
REGEN. HDWD.	11	81.8	577	89.6	0	0	9	0	0	2	0
PASTURE	7	85.7	271	94.1	0	0	1	6	0	0	0
CROP	14	100.0	575	100.0	0	0	0	0	14	0	0
SOIL	5	100.0	291	100.0	0	0	0	0	0	5	0
WATER	13	92.3	193	93.8	1	0	0	0	0	0	12
TOTAL	63		3536		5	9	10	6	14	7	12

OVERALL SAMPLE PERFORMANCE (3412/3536) = 96.5%

OVERALL FIELD PERFORMANCE (58/63) = 92.1%

Table 118. Classification Results for the 30 m MSS Data Using the SECHO Classifier.

TEST CLASS PERFORMANCE

COVER CLASS	NO. OF SAMPLES	PERCENT CORRECT	NUMBER OF SAMPLES CLASSIFIED INTO						
			PINE	HDWD	RGHD	PAST	CROP	SOIL	WATR
PINE	134	75.4	101	28	0	0	0	0	5
HARDWOOD	1495	96.9	13	1448	27	0	0	0	7
REGEN. HDWD.	577	89.1	0	0	514	2	1	57	3
PASTURE	271	91.5	0	0	18	248	0	4	1
CROP	575	95.1	0	0	21	3	547	4	0
SOIL	291	97.6	0	0	0	0	0	284	7
WATER	193	99.5	0	0	0	0	0	1	192
TOTAL	3536		114	1476	580	253	548	350	215

OVERALL PERFORMANCE

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