

Evaluation of Thematic Mapper Data and Computer-aided Analysis Techniques for Mapping Forest Cover

M. ELLEN DEAN and ROGER M. HOFFER

Department of Forestry and Natural Resources
Laboratory for Applications of Remote Sensing
Purdue University, West Lafayette, Indiana 47906

Introduction

Since the launch of the Landsat-1 satellite in 1972, the value of the scanner data obtained from the Landsat satellites has been clearly established. Forest cover types, hydrologic features, agricultural crops and soil patterns, as well as other land use features can be identified and mapped using this satellite data. Because of the quantitative characteristics of such multispectral scanner data and the very large area covered by each frame of Landsat data (over 8.5 million acres), computer-aided analysis techniques are particularly effective for processing Landsat data.

In 1982, a new generation of satellite scanner, called the Thematic Mapper, will be launched aboard Landsat-D. The Thematic Mapper (TM) will have improved spatial and spectral characteristics as compared with the previous satellite scanner systems (i.e. 30 m vs. 80 m spatial resolution and seven relatively narrow vs. four relatively broad wavelength bands). Because of the significant increase in the quantity of data to be obtained and the improved spectral and spatial characteristics of the TM data, it is important to compare the effectiveness of the proposed new Thematic Mapper to the scanner system on board Landsats 1-3 and to define effective data analysis techniques for processing such data.

Objectives

(1) To compare classification results obtained using the best four bands (out of the seven available TM wavelength bands) to results using the four bands most closely approximating the current Landsat scanner.

(2) To compare the classification accuracy of a per-point Gaussian Maximum Likelihood classifier (which classifies each resolution element independently, according to its spectral characteristics) and a per-field classifier (which incorporates the spatial as well as the spectral characteristics of the data into the classification algorithm).

Background

Previous studies have shown that as the number of wavelength bands used to classify MSS data increases, classification accuracy reaches a point of diminishing returns in relation to the computer time required to classify the MSS data (1). This relationship is clearly demonstrated by Figure 1. Even with recent advances in computer technology and software, however, similar relationships are anticipated when analyzing the Thematic Mapper data to be obtained from Landsat-D. Table 1 shows a comparison of the proposed TM channels with those of the current Landsat MSS system. In addition to the increased number of wavelength bands on the TM, it will also have higher spatial resolution. This will allow it to obtain more detailed spectral information from smaller areas on the ground (i.e. resolution elements or pixels) than has previously been possible (5). However, it is possible that higher interclass spectral variability may be introduced with this increase in

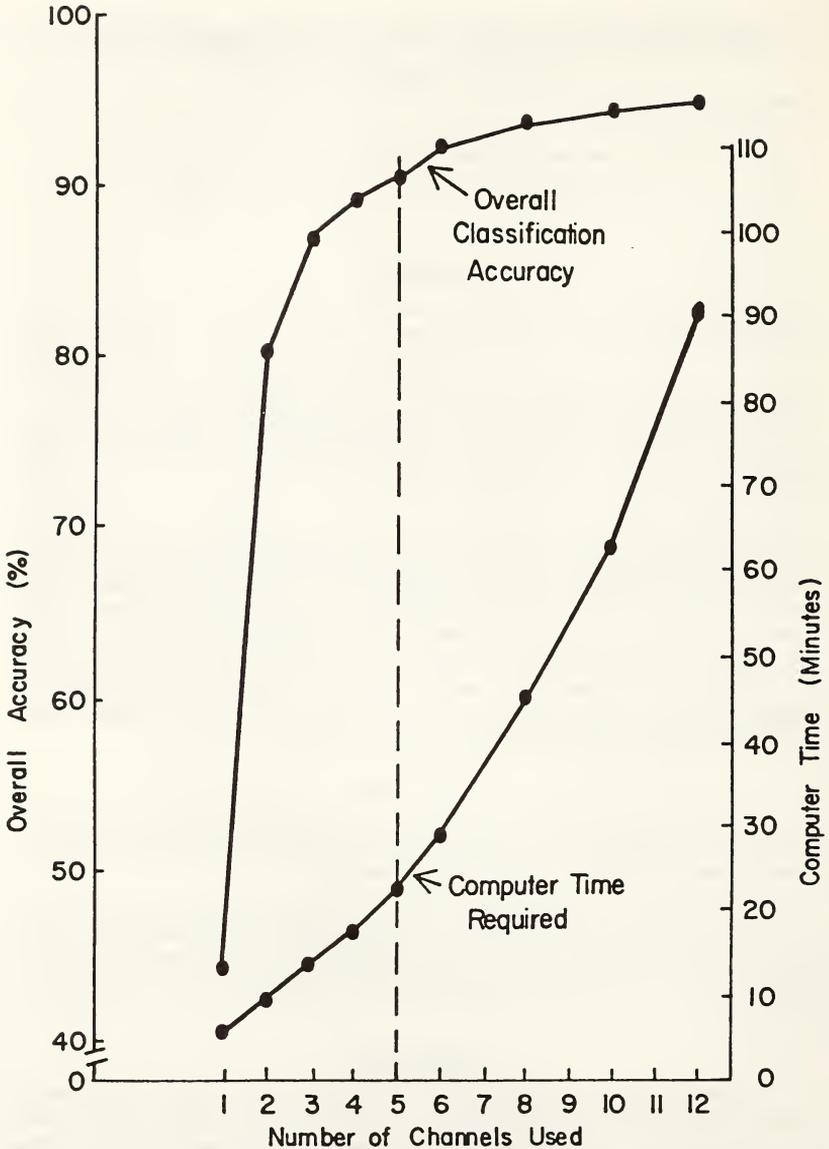


FIGURE 1. Overall classification accuracy and computer time required in relation to the number of channels used (from Ref. 1).

spatial resolution, thus increasing the potential for spectral overlap and intraclass confusion.

Materials and Methods

Data for this study consisted of aircraft multispectral scanner data obtained by NASA's NS001 Thematic Mapper Simulator (TMS). The data were obtained on

TABLE 1. *Wavelength Band Comparisons of the Landsat 1-3, NASA NS001 Scanner and the Landsat D Thematic Mapper Scanner systems (wavelengths are in micrometers).*

	Landsat 1-3	NASA NS001 Scanner	Landsat D Thematic Mapper
Visible	(4) 0.50-0.60 μm	(1) 0.45-0.52 μm	(1) 0.45-0.52 μm
	(5) 0.60-0.70	(2) 0.52-0.60	(2) 0.52-0.60
Near IR	(6) 0.70-0.80	(3) 0.63-0.69	(3) 0.63-0.69
	(7) 0.80-1.10	(4) 0.76-0.90	(4) 0.76-0.90
Thermal Middle IR		(5) 1.00-1.30	
		(6) 1.55-1.75 ¹	(5) 1.55-1.75
		(7) 2.08-2.36	(6) 2.08-2.36
		(8) 10.4-12.5	(7) 10.40-12.5

¹On the May 2, 1979 mission, the 1.55-1.75 μm band was not functional, so on the resultant data tape, the 2.08-2.36 μm band was designated as Channel 6 and the 10.4-12.5 μm band was designated as Channel 7.

May 2, 1979 over a study site in South Carolina near the city of Camden. The predominance of large contiguous tracts of forest (primarily bottomland hardwoods), in addition to minimal topographic relief made this a good site for this study. This area has also been designated by the U.S. Forest Service as one of two primary test sites for evaluating various remote sensing techniques for potential use in forest inventories.

Various cover classes (Table 2) were located in the TMS multispectral data by the analyst and class statistics were obtained using a supervised method for

TABLE 2. *Description of the Cover Classes Defined for the Camden Study Area.*

Cover Class	Description of Cover Class
TUPELO	Water tupelo; generally restricted to narrow ox-bow lakes and other areas of inundated soils.
CROP	Row crops and small grain crops in varying stages of development and maturity.
PASTURE	Pasture and old fields; plant cover varies from healthy improved pasture grasses to senescent forbs and invader species.
SOIL	Bare soil areas associated with agricultural activities; varies in sand, clay, and organic material content as well as moisture content.
HARDWOOD	Old age bottom-land and second growth hardwood; sweetgum is the dominant species in the older age classes with a diverse species composition in the younger age classes.
CLEARCUT	Areas subjected to clearcut forestry practices; ground cover comprised of dry to inundated soils without vegetation, to dense vegetative cover of slash, grasses, shrubs and residual trees. Windrowed slash is common.
PINE	Pine forest areas; the principle species is slash; longleaf, and loblolly are common; age class varies from recently planted (5-10 years) to mature, closed canopy.
WATER	Water; primarily associated with the Wateree River (approximately 70-90 meters in width). Other areas comprising the water class are associated with surface mining and open marsh.

developing training data (1). The computer-generated statistics from the training fields consist of the means and variances of all spectral classes representing the various cover classes in each of the seven channels available. These statistics are used to 'train' the computer and pattern recognition techniques (7) are then applied in order to identify these same spectral classes in the remainder of the MSS data. Test fields of known cover types were also defined for use in evaluating the classification results. These fields were selected using a test grid of dimensions 50 lines by 50 columns. Test blocks, 25 by 25 pixels (i.e. resolution elements) in size, were located in the southwest quadrat of each grid intersection. The largest possible field of every cover type present within each 25 by 25 test cell was located and defined as a test field for that particular class.

To define the 'optimum' four channel subset of the seven available channels, the training statistics were used to define an average transformed divergence (TD) value. This TD value provides a measure of statistical separability of the various spectral classes, and is described in detail in Swain and Davis (7). Pairwise TD values between all spectral classes were averaged for all combinations of four out of the seven TMS channels. The four channel subset with the largest average TD value was then designated as the 'optimum' or 'best' combination for use with this data. Channels 2, 4, 5 and 7 (see Table 1) provided the largest average TD value and were therefore used as the optimum set with which to compare channels 2, 3, 4 and 5, (which were used to stimulate the existing Landsat MSS system) in all subsequent analyses.

The first of the two classifiers used in this study was the GML or Gaussian Maximum Likelihood classifier, a widely used classification algorithm in remote sensing applications. Assumptions upon which this algorithm is based include an absolutely continuous n-variate spectral response vector and multivariate normal class conditional probability density functions (PDF's) (7). Usually these assumptions are not completely satisfied due to the quantification of the spectral response in each channel into distinct response levels, and because of the inherent variability in spectral response of natural cover features. However, deviations from these assumptions are often slight and many classifiers, including the GML, are 'robust' in their tolerance of such violations (4), (7).

The GML classifier is based upon the Bayes' optimal strategy which minimizes the average loss over the entire set of classifications to be performed, i.e. it minimizes the probability of error over the entire data set to be classified and, in so doing, maximizes the probability of correct classification (PCC) (7). In general, this classifier is the most accurate classifier available. However, because the individual pixels are classified based upon spectral information alone, pixels within a particular spectral class may deviate from the class conditional PDF (probability density function) for that spectral class enough so as to be misclassified into another cover class. In other words, one spectral class may represent more than one cover class due to the high interclass variabilities of those cover classes; i.e. significant spectral overlap between two or more cover classes may occur. Consequently, a decision rule such as the GML, which is based upon spectral information alone, may have poor classification performance if there is poor spectral separability between cover classes.

One method of alleviating such difficulties is to incorporate additional information, such as contextual information about adjacent pixels, into the decision rule. The second classifier used in this study, the ECHO (Extraction and Classification of

Homogeneous Objects) classifier, incorporates both spectral and spatial information in the classification sequence and is divided into the following two basic steps:

1) The MSS imagery is partitioned into areas or blocks of statistically similar pixels—a conjunctive approach is used in which small initial $n \times n$ homogeneous cells are progressively annexed to adjacent homogeneous cells of similar spectral response until a specified annexation threshold (defined by the analyst) is exceeded.

2) Once the areas of similar spectral characteristics have been determined, statistics representing the PDF's of each of these areas are calculated and compared with the PDF's characterizing all the original m spectral classes, i.e. those spectral classes used to 'train' the computer, and each homogeneous area is then classified, using an extension of the GML algorithm, into that cover class which its PDF most closely approximates.

If at any time a cell of initial $n \times n$ dimensions fails a specified homogeneity criteria, then each individual pixel within that cell will be classified using the standard per-pixel GML classifier. For a detailed discussion of the procedure please refer to Kettig and Landgrebe (2), Landgrebe and Erickson (3), and Latty (4).

An arcsin transformation in conjunction with a Newman-Keuls range test was used to compare the classification accuracies achieved (i.e. the PCC values attained) (6).

Results and Discussion

Tables 3, 4 and 5 present the results associated with each of the classifications performed in this study along with the number of test samples and the PCC (probability of correct classification) for each cover class. The PCC for each cover class is found by dividing the sum of correctly classified samples (test pixels) by the total number of test pixels for that cover class. Likewise, overall classification performances are obtained from the sum of all correctly classified pixels from all cover classes divided by the entire number of test samples, i.e. 11,202. Table 6 summarizes the results of all classifications performed and also indicates the results of the Newman-Keuls range test.

TABLE 3. *Classification results based on test field accuracy using the Gaussian Maximum Likelihood (GML) classification algorithm and simulated Landsat wavelength bands (Channels 2, 3, 4, and 5).¹*

GROUP	No. of SAMPS	PCT CORCT	PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATER
PINE	775	92.6	718	4	0	35	16	0	0	2
HDWD	7951	89.1	273	7081	174	316	18	8	57	24
TUPE	126	78.3	0	8	94	7	8	2	0	1
CCUT	370	51.4	81	0	0	190	77	1	15	6
PAST	350	71.1	0	28	0	49	249	24	0	0
CROP	324	76.4	0	0	0	3	82	278	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	11,202									

$$\text{Overall Performance} = \frac{9777}{11,202} = 87.3\%$$

¹Channel 2 = 0.52-0.60 μm ; Channel 3 = 0.63-0.69 μm ; Channel 4 = 0.76-0.90 μm ; and Channel 5 = 1.00-1.30 μm .

TABLE 4. *Classification results based on test field accuracy using the Gaussian Maximum Likelihood (GML) classification algorithm and the "Best 4" wavelength bands (Channels 2, 4, 5, and 7).¹*

GROUP	No. of PCT		PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATER
	SAMPS	CORCT								
PINE	775	91.0	705	4	0	40	26	0	0	0
HDWD	7951	88.0	280	6998	146	375	65	26	60	1
TUPE	126	59.2	0	4	75	7	5	34	0	1
CCUT	370	60.5	48	0	0	224	49	0	49	0
PAST	350	82.6	0	2	1	38	289	20	0	0
CROP	324	77.2	0	1	7	2	63	250	0	0
SOIL	1006	85.6	0	0	0	123	19	0	861	0
WATER	300	78.7	0	3	2	55	1	0	3	236
TOTAL	11,202									
			Overall performance = $\frac{9638}{11,202} = 86.04\%$							

¹Channel 2 = 0.52-0.60 μm ; Channel 4 = 0.76-0.90 μm ; Channel 5 = 1.00-1.30 μm ; and Channel 7 = 10.4-12.8 μm .

The superscripts in Table 6 indicate the statistical evaluation of the results obtained within a particular cover class and for overall performances of the three classifications using the Newman-Keuls range test at an alpha level of 0.10. Different superscripts indicates that the results for that cover type or for the overall performances were significantly different; those cover types having the same superscripts are not statistically different.

TABLE 5. *Classification results based on test field accuracy using the ECHO classification algorithm and the "Best 4" wavelength bands (Channels 2, 4, 5, and 7).¹*

GROUP	No. of PCT		PINE	HDWD	TUPE	CCUT	PAST	CROP	SOIL	WATER
	SAMPS	CORCT								
PINE	775	92.9	720	1	0	18	36	0	0	0
HDWD	7951	92.8	169	7382	40	250	92	18	0	0
TUPE	126	60.3	0	9	76	6	3	31	0	1
CCUT	370	58.9	41	0	0	218	65	0	46	0
PAST	350	85.7	0	1	0	35	300	14	0	0
CROP	324	81.5	0	0	8	0	52	264	0	0
SOIL	1006	85.7	0	1	0	120	20	0	862	3
WATER	300	77.7	0	3	2	58	1	0	3	233
TOTAL	11,202									
			Overall Performance = $\frac{10055}{11,202} = 89.7\%$							

¹Channel 2 = 0.52-0.60 μm ; Channel 4 = 0.76-0.90 μm ; Channel 5 = 1.00-1.30 μm ; and Channel 7 = 10.4-12.8 μm .

TABLE 6. *Summary Comparison of Classification Results (% Accuracy of Test Fields).*

Cover-Type	No. of Samps	Wavebands and Classifier Used		
		"Landsat"	"Best 4"	"Best 4"
		Wavebands, ¹ GML Classifier	TM Wavebands, ² GML Classifier	TM Wavebands ECHO Classifier
PINE	775	92.6% ^{a3}	91.0% ^a	92.9% ^a
HDWD	7951	89.1% ^a	88.0% ^b	92.8% ^c
TUPE	126	78.3% ^a	59.2% ^b	60.3% ^b
CCUT	370	51.4% ^a	60.5% ^b	58.9% ^b
PAST	350	71.1% ^a	82.6% ^b	85.7% ^b
CROP	324	76.4% ^a	77.2% ^a	81.5% ^a
SOIL	1006	90.3% ^a	85.6% ^b	85.7% ^b
WATER	300	86.3% ^a	78.7% ^b	77.7% ^b
OVERALL		87.3% ^a	86.0% ^b	89.7% ^c

¹"Landsat" Wavebands included 2 visible and 2 near infrared wavebands—0.52-0.60, 0.63-0.69, 0.76-0.90, and 1.0-1.3 μm .

²The "Best 4" TM Wavebands were defined using a Transformed Divergence Algorithm as a measure of statistical separability. Of the 7 TM Wavebands available, the "Best 4" included 1 visible, 2 near infrared, and 10.4-12.5 μm .

³For each cover type, or for the overall classification results, different superscript letters indicate a statistically significant difference, based upon a Newman-Keuls range test with $\alpha = 0.10$. Comparison between Col. 1 and Col. 2 provides an indication of the effect of waveband combination, while comparison between Col. 2 and Col. 3 indicates effect of the classification algorithm used.

The first and second columns of classification results shown in Table 6 compare the Landsat channels with the 'best 4' selected by a maximum average TD value. The second and third columns similarly compare the GML classifier with the ECHO classifier. It is interesting to note that even though the overall performance obtained by the ECHO classifier was significantly better than either of the other classifications, only the Hardwood cover class showed significant difference between the GML and ECHO classifiers using channels 2, 4, 5 and 7. This might indicate that with cover classes of large spectral variability, such as the hardwood category, a significant increase in classification performance can be obtained using a per-field classifier. The other cover classes were much more spectrally distinct, i.e. had lower spectral variability, and hence performed as well using either classifier. The increase in overall classification performance was subsequently a result of the increase in the performance of the hardwood category, largely because the number of hardwood pixels greatly exceeded those of all other categories and therefore carried more weight in the calculation of overall performance. In addition, these results imply certain limitations associated with the average TD values as criteria for selecting an optimal subset of channels; i.e., in this study, even though channels 2, 4, 5 and 7 were chosen as the 'optimal' using an average TD value, channels 2, 3, 4 and 5 (simulated Landsat) still achieved higher overall classification accuracies using the GML classifier. One possible explanation for this is that both the transformed divergence measurement and the GML

classification algorithm incorporate class a priori probabilities in their calculations. In this and many other remote sensing applications, these class a priori probabilities are assumed to be equal, but this is rarely the case. Therefore, those classes with higher class priori probabilities of occurrence may be discriminated against in favor of those classes of lower a priori probabilities, thus resulting in a lower overall classification performance.

Conclusions

The conclusions reached in this study can be summarized as follows:

- 1) Increased classification performances were demonstrated for some cover types and for the overall classification performance when using the ECHO classifier, as compared to the per-point GML classifier. Although statistically significant, the increased classification performances were relatively small in most cases and may be essentially unimportant from the user's standpoint.
- 2) The ECHO classifier is particularly effective in classifying those cover types of relatively high spectral variability, such as the hardwood cover class category in this study.
- 3) For MSS data of higher spatial resolution, such as will be obtained by the Thematic Mapper on Landsat-D, per-field algorithms such as ECHO, which utilize both the spectral and spatial characteristics of the data, should be effective in achieving improved classifications of areas of forest cover.
- 4) As a measure of statistical separability the transformed divergence (TD) value has certain limitations when applied to MSS data sets and therefore may not be a reliable indicator of the optimum subset of channels to use in the classification if the areal extent of the different cover types involved are significantly different.

Acknowledgment

This research was supported by NASA Contract 9-15889.

Literature Cited

1. CCGESHALL, M.E. and R.M. HOFFER. 1973. Basic Forest Cover Type Mapping using Digitized Remote Sensor Data and ADP Techniques. LARS Information Note 030573, LARS, Purdue University, West Lafayette, IN. 131pp.
2. KETTIG, R.L. and D.A. LANDGREBE. 1975. Classification of Multispectral Image Data by Extraction and Classification of Homogeneous Objects. LARS Information Note 062375, LARS, Purdue University, West Lafayette, IN. 18pp.
3. LANDGREBE, D.A. and J.D. ERICKSON. 1977. Final Technical Report: NASA Contract NAS9-14970, LARS, Purdue University, West Lafayette, IN.
4. LATTY, RICHARD S. 1981. Computer-Based Forest Cover Classification Using Multispectral Scanner Data of Different Spatial Resolutions. Master of Science Thesis, Purdue University, West Lafayette, IN. 187pp.
5. SALOMONSON, V.V. 1978. Landsat-D Systems Overview. Proceedings of the Twelfth International Symposium on Remote Sensing of the Environment, ERIM. pp. 371-385.
6. STEELE, R.G.D. and J.H. TORRIE. 1960. Principles and Procedures of Statistics. McGraw-Hill Publishing Co., New York, N.Y. 418pp.
7. SWAIN, P.H. and S.M. DAVIS (editors). 1978. Remote Sensing: The Quantitative Approach, McGraw-Hill Publishing Co., New York, N.Y. 364pp.