Evaluation of Landsat Thematic Mapper Data for Classifying Forest Lands

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With the launch of Landsat-1 in July of 1972, man entered a new era for obtaining information about earth resources. Landsat-1 was the first unmanned satellite designed specifically for collecting data about earth resources on a global, repetitive, multispectral basis.

Technology developed rapidly during the seventies for processing and analysis of the digital multispectral scanner data that was collected by Landsat. There was a great deal of interest in the multispectral data—commonly referred to as MSS data—and many applications were developed. Two more Landsat satellites with MSS sensors were launched before the end of the decade.

Another milestone in Earth resource observations occurred in July 1982 when the fourth satellite in the Landsat series was launched. In addition to a MSS sensor, a new improved sensor called the Thematic Mapper (TM) was carried aboard Landsat-4. The TM sensor has improved spatial resolution and spectral dimensionality as compared to the MSS sensor (see Table 1). The MSS sensor collects data in only four

Table 1. Comparison of Landsat Scanning Sensors. Adapted from (2).

	Thematic Mapper (TM)			Multispectral Scanner (MSS)		
Spectral Band Designation	Wavelength Range	Spectral Region	Ground IFOV	Wavelength Range	Spectral Region	Ground IFOV
1	0.45-0.52 μm	Visible Blue	30 m	0.5-0.6 μm	Visible Green	80 m
2	0.52-0.60 μm	Visible Green	30 m	0.6-0.7 μm	Visible Red	80 m
3	0.63-0.69 μm	Visible Red	30 m	0.7-0.8 μm	Near Infrared	80 m
4	0.76-0.90 μm	Near Infrared	30 m	0.8-1.1 μm	Near Infrared	80 m
5	1.55-1.75 μm	Middle Infrared	30 m			
6	2.08-2.35 μm	Middle Infrared	30 m			
7	10.40-12.50 μm	Thermal Infrared	120 m			

spectral bands—two in the visible and two in the near infrared region of the electromagnetic spectrum-whereas the TM sensor collects data in seven spectral band—three in the visible, one in the near infrared, two in the middle infrared, and one in the thermal infrared region. Because of the relatively low level of energy emitted in the thermal infrared region, the spatial resolution of this band is 120 meters—much larger than the other TM or MSS bands. The resolution, expressed as instantaneous field of view (IFOV), for the remaining six bands of the TM sensor is 30 meters as opposed to approximately 80 meters for the MSS sensor.

Many studies, including those by Hoffer et al. (4), Kalensky and Scherk (5), and Strahler et al. (7), have shown that MSS data is useful for classifying geographic areas into broad cover types. Given the improvements of TM data, the purpose of this study was to determine the utility of TM data for classifying a predominantly forested area into broad cover types. The objectives were twofold:

1) Evaluate the utility of wintertime Thematic Mapper data for classifying forest and other broad cover types using supervised training statistics and a minimum distance classifier.

2) Determine the value of different wavelength bands and combinations of bands for classifying the various cover types.

Procedures

The TM data were obtained by Landsat 4 on December 18, 1982. The study area was composed of St. Regis Corporation land in Baker County, Florida. Reference data used to interpret the TM data included 1:58,000 color infrared aerial photographs obtained on January 24, 1983, and a forest stand map that included stand boundaries, species, and ages. This map and the associated information was provided by the St. Regis Forest Resource Information System (FRIS) Center. Field visits (August and October 1984) to the study area by the authors provided a better understanding of the characteristics of the forest and other cover types present. Comparisons of the reference data and the spectral cluster maps proved to be very beneficial when analyzing and interpreting the TM data.

The study area was predominantly forested. Major forest types in the area were slash and longleaf pine (the former often in plantations), and also pondcypress and mixed hardwoods principally occurring in shallow ponds or bays (1). A small number of agricultural areas were located within the study area and a small amount of exposed water was present.

After viewing the aerial photographs, the St. Regis forest stand map, and a grayscale printout of the TM data, it was determined that all the land cover types of the study area could be divided into six broad cover type classes, called information classes. The informational classes of interest included: three classes of pine forest—Young (0 to 5 years), Medium-Aged (6 to 10 years), and Older (11 or more years); Deciduous Forest; Agricultural Areas; and Water. Because of spectral variability within some of these informational classes, it was determined that nine spectral classes were needed in order to adequately represent the informational classes defined.

As indicated previously, at any one instant of time, the Thematic Mapper scanner on the Landsat satellite measures the reflectance and thermal emission in each of seven wavelength bands over a resolution element (or pixel) that represents an area on the ground of 30 meters by 30 meters (120 meters by 120 meters for band 7). These measurements provide the sets of data values that define the spectral patterns of the various cover types on the ground. In order to use a computer to classify satellite spectral data, the analyst must "train" the computer to recognize specific spectral patterns and then classify the data having these defined spectral patterns into the informational classes of interest. Such computer classification is based upon statistical pattern recognition theory—a well-documented body of knowledge used in many disciplines (8).

The first step in computer classification involves the definition of a set of training data that statistically represents the informational classes of interest. This step is one of the most critical parts of the entire classification procedure (3).

In our analysis, we started by studying the St. Regis forest stand map and color infrared photographs and selecting potential training areas. Each training area involved a single cover type. Several training areas were defined for each cover type, so every spectral class in the study area would be represented in the training data set. The digital format TM data were then displayed on a Comtal Vision One/20 digital display unit as a color infrared composite (the digital equivalent of a color infrared photograph).

The pixel coordinates of potential training areas were then designated. Each training area consisted of several contiguous pixels, and at least three such training areas were defined for each spectral class. Additional training areas were defined, if necessary, so that a minimum of 70 pixels (10 times the maximum number of wavelength bands used) would be included in the training statistics for each class, in-so-far as possible.

The statistical characteristics of the training areas were then defined using the LARSYS software system. These statistics included the mean and covariance matrix of the seven bands for each spectral class (6), and provided the information necessary for computer classification of the various informational classes.

The next step involved the actual classification of the TM data. The classification process involves the use of an algorithm to compare the training data statistics to the reflectance and emission values measured by the TM scanner for each pixel in the entire data set. Several classification algorithms are available within the LARSYS software. For this study, we used the relatively simple and fast minimum Euclidean distance classification algorithm of the CLASSIFYPOINTS processor. A detailed description of this processor and the entire LARSYS software system is documented by Phillips (6).

To test quantitatively the accuracy of the classifications, a set of "test areas" were defined. Each test area consisted of a block of pixels thought to be representative of the six informational classes present. (Thus, a test area is very similar to a training area, but is used for an entirely different purpose.) A systematic statistical sampling procedure was used to define the test data locations so that the training areas and test areas were obtained from mutually exclusive locations in the data set. Fifty-three test fields totalling 2372 pixels were thus defined for this study.

In order to evaluate the utility of the various TM wavelength bands for purposes of computer classification, a method to assess the information content of each wavelength band and band combination was required. Part of the LARSYS software (i.e. SEPARABILITY) involves a "feature selection" technique which allows the analyst to determine the optimum combination of bands to use, given any set of one through "n" wavelength bands. Transformed divergence (TD), a statistical distance measure, is calculated between all possible pairs of spectral classes for the specific combination of wavelength bands being considered. When the TD is large (e.g. values above 1900; maximum is 2000), there is a high probability that the two spectral classes can be discriminated and a correct classification will result (8).

For this study, the "best" combinations of wavelength bands for each set of the one through seven bands of TM data were defined using the average and minimum TD values. Large average and minimum TD values were desirable as this indicated that the classes were spectrally separable. Generally, only the minimum TD values defined for each pair of spectral classes representing *different* informational classes (rather than spectral classes within the *same* informational class) were utilized.

Based upon the Transformed Divergence results for determining the optimum one through seven wavelength band combinations, seven separate classifications of the data were then obtained, and the results were quantitatively summarized using the test fields that had been previously defined. The key point here is that the same training and test data were used for each of the seven classifications—the only variables were the number and combinations of wavelength bands utilized.

Results and Discussion

The "best" channel combinations and their average transformed divergences are summarized in Table 2. The performances for each of the seven classifications were assessed using the classification results for the test fields. Table 3 is the LARSYS-generated classification performance matrix for the "best" combination of four bands,

TABLE 2. "Best" wavelength band combinations selected and their associated average and minimum transformed divergences.

CHANNELS		TRANSFORMED DIVERGENCE	
Number	Bands	Minimum	Average
1	5	532[1]	1761
2	4,5	1781	1980
3	4,5,7	1837[1]	1987
4	3,4,5,7	1938[1]	1991
5	3,4,5,6,7	1950[1]	1992
6	2,3,4,5,6,7	1952[1]	1993
7	1,2,3,4,5,6,7	1955[1]	1993

[1]Lower transformed divergence did occur between two spectral classes within the same information class.

namely, bands 3, 4, 5, and 7, showing how the test pixels were classified. Such a matrix was generated for each of the seven classifications. The classification results for all classifications are summarized in Table 4.

TABLE 3. Classification Performance Matrix for the "Best" Combination of Four Bands. (F1 = Young Pine Forest, F+ = Medium-Aged Pine Forest, F* = Older Pine Forest, FD = Deciduous Forest, AA = Agricultural Areas, WW = Water)

FOREST LABORATORY FOR APPLICATIONS OF REMOTE SENSING OCT. 31, 1984
RESULTS 4 PURDUE UNIVERSITY 08 48 01 AM
LARSYS VERSION 3

CLASSIFICATION STUDY 430540387 CLASSIFIED OCT. 31, 1984
CLASSIFICATION WRITTEN ON DISK
CHANNELS USED

Channel 3	Spectral Band	0.63 TO 0.69	Micrometers	Calibration Code = 1	CO = .0
Channel 4	Spectral Band	0.76 TO 0.90	Micrometers	Calibration Code = 1	CO = .0
Channel 5	Spectral Band	1.55 TO 1.75	Micrometers	Calibration Code = 1	CO = .0
Channel 7	Spectral Band	10.40 TO 12.50	Micrometers	Calibration Code = 1	CO = .0

CLASSES

	SPECTRAL CLASS	INFORMATION CLASS		SPECTRAL CLASS	INFORMATION CLASS
1	F1	F1	6	A1	AA
2	F+	F+	7	A2	AA
3	F*	F*	8	A3	AA
4	FD	FD	9	W	WW
5	FDC	FD			

TEST CLASS PERFORMANCE

INFORMATION CLASS	NO OF SAMPS	PCT. CORCT	NUMBER OF SAMPLES CLASSIFIED INTO F1	F+	F*	FD	AA	WW
1 F1	351	71.8	252	0	0	0	99	0
2 F+	235	98.3	3	231	0	0	0	0
3 F*	1141	99.1	0	5	1131	5	0	0
4 FD	432	95.4	0	5	15	412	0	0
5 AA	207	97.1	6	0	0	0	201	0
6 WW	6	83.3	0	0	0	1	0	5
TOTAL	2372		261	241	1147	418	300	5

Overall performance (2232/ 2372) = 94.1
Average Performance By Class (545.0/ 6) = 90.8

10103 CPU TIME USED WAS 3.813 SECONDS (LARSMN)

TABLE 4. Summary of Classification Results.

	Number of Test Pixels	Classification Performance (%) — Number of TM Wavebands (Specific TM Wavebands)						
		1 (5)	2 (4,5)	3 (4,5,7)	4 (3,4,5,7)	5 (3-7)	6 (2-7)	7 (1-7)
Young Pine Forest	351	68.9	72.4	72.4	71.8	66.4	66.4	64.7
Medium-Aged Pine Forest	235	70.6	97.4	97.4	98.3	98.3	98.3	99.1
Older Pine Forest	1141	81.3	98.9	98.9	99.1	99.6	99.6	99.5
Deciduous Forest	432	93.8	95.4	95.6	95.4	95.1	95.1	94.9
Agriculture Areas	207	81.2	97.1	97.1	97.1	96.1	96.1	96.6
Water	6	83.3	83.3	83.3	83.3	83.3	83.3	83.3
Overall Performance	2372	80.7	94.0	94.1	94.1	93.4	93.4	93.2
Average By Class		79.9	90.8	90.8	90.8	89.8	89.8	89.7

The overall performance for the classifications was high in all cases, except when only one TM wavelength band was used. Disregarding the one-band classification, the classification performance values for the individual informational classes were also very high except for the Young Pine Forest and Water classes. The low performance for the Young Pine Forest class is due to the fact that a significant number of pixels were being misclassified into the Agricultural Areas class. This is not surprising since the class Young Pine Forest includes recently harvested areas which consist of residual understory vegetation mixed with bare soil. This is spectrally similar to the situation often found in Agricultural Areas where agricultural crops and bare soil are mixed. This confusion is illustrated in Table 3 where F1 is the Young Pine Forest information class and AA is the Agricultural Areas information class. The relatively low classification performance for water stems from the fact that there was very little exposed water in the study area. With LARSYS, the test field must be rectangular. In the process of selecting a rectangular test field for a small, non-rectangular water body, one pixel (of six) was apparently an edge pixel—a mixture of two spectral classes—and was therefore misclassified. The small number of Water test pixels is directly related to the small amount of exposed water in the study area.

Conclusions

The results of this study show that:

Forest and other broad cover type groups can be classified with a high degree of accuracy using wintertime Landsat Thematic Mapper data.

Even the relatively simple minimum distance classification algorithm achieved highly accurate classification results for the six informational classes defined.

The 1.55-1.75 μm middle infrared wavelength band was found to be the single most useful band for discrimination between the spectral classes defined.

The "best" combination of two wavelength bands included a band in the near infrared (0.76-0.90 μm) and a band in the middle infrared (1.55-1.75 μm) portion of the electromagentic spectrum.

The 10.4-12.5 μm thermal infrared wavelength band appears to provide significant additional information for the classification process.

The "best" combination of four wavelength bands included one band from each of the four major portions of the spectrum—visible, near infrared, middle infrared, and the thermal infrared.

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