Use of Multitemporal Spectral Profiles in Agricultural Land-Cover Classification

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ABSTRACT: A range of single date and multitemporal classification approaches was compared using Landsat MSS data acquired during the 1979 growing season in the vicinity of Green Bay, Wisconsin. In addition to evaluating the traditional supervised and unsupervised classification strategies typically applied in such efforts, an unsupervised multitemporal ratio approach was developed. This involved the use of multidate ratioed data in a clustering algorithm sensitive to image texture. A spectral variance threshold for a moving 3 by 3 pixel window in the image data was used to isolate homogeneous areas for cluster center definition. A temporal ratio profile for each cluster center was constructed and then labeled according to the local crop calendar. The paper highlights not only the ease of this procedure, but also its superior accuracy and consistency as compared to the traditional classification procedures tested. The practicality of such multitemporal analyses will be greatly enhanced by the "on demand" image acquisition features of future satellite systems such as SPOT.

INTRODUCTION

PARTICULARLY in the past decade, remote sensing employing digital Landsat data has developed at a rapid pace. It has become a practical tool for monitoring the environment and assessing our natural resources in a number of application areas. Nevertheless, computer-generated land-cover classifications require significant improvement in both their accuracy and specificity in order to be used operationally in many applications. One facet to the solution of this problem is to improve the quality of the raw data. This has been initiated with the launch of the Landsat Thematic Mapper and will continue with the launch of the forthcoming SPOT satellite.

Equally important is the development of new methodologies to analyze and classify the data. This paper deals with the latter issue in the context of evaluating multitemporal MSS data analysis procedures for agricultural land-use/land-cover mapping. The basic need for a multitemporal approach stems from the fact that single date analyses rarely permit accurate classification of all cover types of interest in an agricultural setting over the course of a growing season. This is especially true when a diverse agricultural system is monitored.

The processing of multitemporal Landsat data normally involves two basic elements: techniques for data compression and techniques for image classification. Following is a very brief summary of representative previous research involving techniques for compressing, analyzing, and classifying multitemporal data:

(1) All available channels from various dates have been used for classification without initial data compression (Bizzell *et al.*, 1975; Abotteen, 1977; Wall *et al.*, 1979; Bauer *et al.*, 1979; Chandrasekhar and Maruthachalam, 1978; Hixson *et al.*, 1980; Dawbin and Beach, 1981; Mergerson, 1981).

(2) Selected channels of data have been used for classification, with the combination of Band 5 and Band 7 producing improved results (Abotteen, 1977; Tanaka *et al.*, 1978; Bauer *et al.*, 1979; Hixson *et al.*, 1980).

(3) Principal component transformation has been applied to reduce multitemporal data to fewer dimensions, with as much as 99 percent of the original information preserved along the first four axes (Abotteen, 1977; Merembeck and Borden, 1978).

(4) Tasselled-cap transformation and other measures of greenness have been employed to emphasize certain features in the data for analysis or classification (Richardson and Wiegand, 1977; Malila *et al.*, 1980; Badhwar *et al.*, 1982).

(5) Various canonical transformation techniques have been employed to transform multitemporal data along the most separable axes, with the first three or four axes used for classification (Lachowsky and Borden, 1973; Merembeck and Turner, 1979).

(6) Profile modeling procedures have been used to construct a graphic trajectory or curve of temporal data based on the Tasseled Cap Theory and to fit a ref-

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erence profile for identification. The goodness-of-fit has been based on either a nonparametric method or a statistical procedure involving a polynomial curve fitting (Crist and Malila, 1980; Tubbs, 1980; Crist and Malila, 1981; Woolford, 1983).

(7) Angular measure classification procedures have employed the Green Vegetation Index and the Soil Brightness Index of data plotted in two dimensions. A simple angular distribution algorithm has been used for feature recognition, akin to the procedures used for recognition of handwritten characters (Misra and Wheeler, 1977, 1978; Wheeler and Misra, 1980).

(8) Delta classifiers have been used to reduce four-channel data to two-dimensional mean vectors. The temporal trend of the mean vectors has then been plotted on a triangular graph for classification by means of a simple decision rule (Engvall *et al.*, 1977).

(9) A range of transformation algorithms based on various biophysical principles has also been applied in image classification (e.g., Bodner,1979).

Some of the classification techniques described above (6, 7, 8) involve graphical shape, instead of statistical value, as the basis for discrimination. While these techniques have shown great promise, various problems have typically limited their accuracy in comparison to the more "traditional" classification approaches (1, 2, 3, 4, 5).

The study described herein evaluated a technique which merges the concepts of unsupervised classification and multitemporal profiling. Accordingly, the procedure can be viewed as the marriage between a graphical shape approach and a statistical approach. The method was tested against the traditional methods of single-date and multitemporal classification.

STUDY SITES/DATA PREPROCESSING

Two study sites were used in this analysis, both located on the outskirts of the city of Green Bay, Wisconsin. The first site, located west of the city, is approximately 145 square kilometres (56 square miles) in size. The second site, with an area of approximately 458 square kilometres (177 square miles) is located to the south of the city. Based on a screening of all available Landsat MSS data of the areas, we chose to use the images of 20 May, 25 June, 5 July, and 6 September 1979 for this study. These images represented different stages of the same growing season; they were cloud free, and of good quality. Two aerial photographic missions were also executed over the study sites on 23 April and 16 September of the same year. The aerial photographs served as convenient reference for training and verification purposes. Additional ground surveys of the study sites were conducted at various times during the summer to verify crop development stages.

The farming practices of the Green Bay area of Wisconsin are typical of the dairy belt. Corn was planted during the period from mid-May to mid-June in 1979. It grew to knee height by 4 July. However, it did not have significant ground cover until mid-July. The real growth of biomass was from mid-July to mid-August, which was reflected by the increase in intensity of reflectance of the infrared band. Alfalfa was the dominant hay crop. Winter survival was critical to the alfalfa stands. First harvest was in mid-June, with another harvest in September. In some fields, three harvests were possible during the growing season. The extreme high reflectance of mature stands and the fluctuation of spectral reflectance due to harvesting is the key point in identifying alfalfa. Oats were planted as early as mid-April, so it would be possible to detect the greenness of oat fields in June data. The most active harvesting period was from 5 August to 20 August. Pasturing began in early May and continued well into fall. Pasturing conditions were best in late May and during June, when rainfall and temperature were most favorable for the development of grass. Hotter and drier weather in July caused pasture conditions to deteriorate and remain poor during August.

The hardware and software used for the image analysis reside at the Environmental Remote Sensing Center (ERSC) of the Institute for Environmental Studies, University of Wisconsin-Madison. The heart of this facility is a Digital Equipment Corporation PDP 11/45 minicomputer which runs under the UNIX operating system. The computer supports a Stanford Technology Corporation (STC) model 70 color graphic processor, which has memory for three 8-bit image planes, each up to 512 by 512 pixels in size. The graphic processor also contains hardware for onboard array processing of images.

Preprocessing involved the computation of radiance values for each data set and a normalization of the solar elevation effects present in the multitemporal images (Robinove, 1982). A correction for atmospheric effects proved to be an elusive task. While much previous work has been done on this problem in the past (Rogers *et al.*, 1973; Dana, 1976; Turner, 1978), unfortunately, the correction algorithms proposed by these studies generally dictate the measurement of parameters concerning atmospheric conditions coincident with image acquisition. In the absence of such supplementary data, we resorted to a method suggested by Scarpace *et al.* (1978). Sample pixels, the reflectances of which are assumed to not change through time (such as airport runways), were extracted from each band of the preprocessed images. Any difference in observed radiances of these surfaces between any two images acquired at different dates was assumed to be due to a change in path radiance and/or atmospheric attenuation. The sample pixel values for the calibration area were averaged for each band of each image. The image yielding the smallest value of this average was used as a standard which was subtracted from the average values observed in the same band on the other dates. The resulting remainders were considered to be the path radiance present in each image. These path radiance values were then subtracted from all the pixels of the respective images. This procedure represented at least a first-order correction for additive atmospheric effects. Residual multiplicative effects were necessarily ignored in the subsequent traditional analyses we performed.

Geometric registration of the various images involved the selection of control points, the computation of coordinate transformation parameters, and the resampling of the image data. An affine coordinate transformation was used, and a nearest-neighbor interpolation program was employed to resample all images into the location and orientation of a single master image (6 September). To permit a visual check on the accuracy of the registration, the master image and the resampled images were aligned one at a time on the STC color monitor. If the two images misregistered by more than one pixel, the entire registration process was repeated until sub-pixel registration accuracy of all dates was obtained.

CLASSIFICATION

As mentioned earlier, the classification of multitemporal data involves techniques for feature extraction and techniques for classification (Figure 1). Feature extraction allows us, on the one hand, to emphasize the temporal trends in the data and, on the other, to reduce the dimensionality of the data. In this study we evaluated a number of biomass transformations, or vegetation indices, in order to emphasize the relative greenness of the land-cover classes of interest. This evaluation was done on a representative subset of test data, and it was determined that the ratio of M7/M5 and the Green Vegetation Index Transformation (GVI) (Kauth and Thomas, 1976) provided the most useful temporal discrimination for our situation. Figure 2 depicts the M7/M5 ratio and the GVI temporal profile for a sample of corn pixels on the various dates of imaging. It was this type of transformed data that we used in our multitemporal unsupervised and supervised classification.

The unsupervised analysis we employed involves moving a 3 by 3 window across the image to search for homogeneous areas to serve as "training data" or nuclei for clustering. The means and variances of these window areas are then computed. The image analyst can define the total number of clusters to be found, the highest acceptable variance for the 3 by 3 blocks contributing to a cluster, and the statistical distance below which two neighboring clusters should be merged. The statistical distance (used in our algorithm) is a "normalized distance between

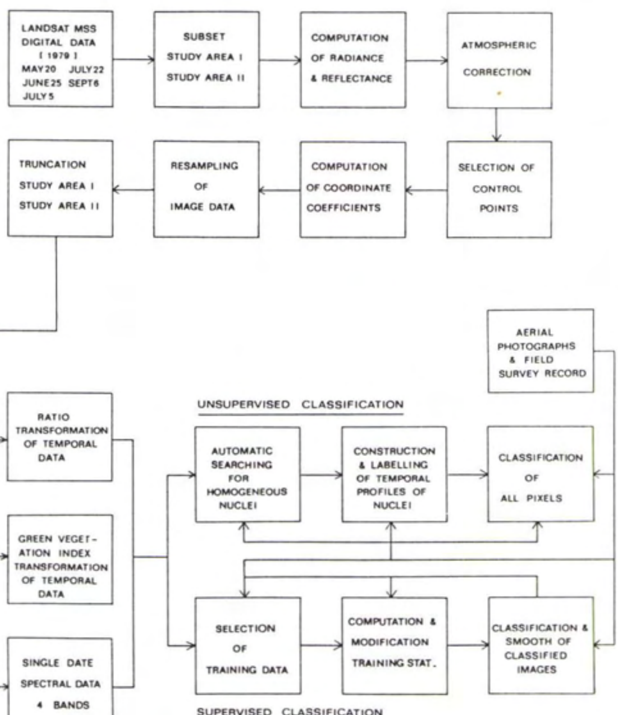

FIG. 1. Preprocessing, feature extraction, and classification procedures for multitemporal Landsat data.

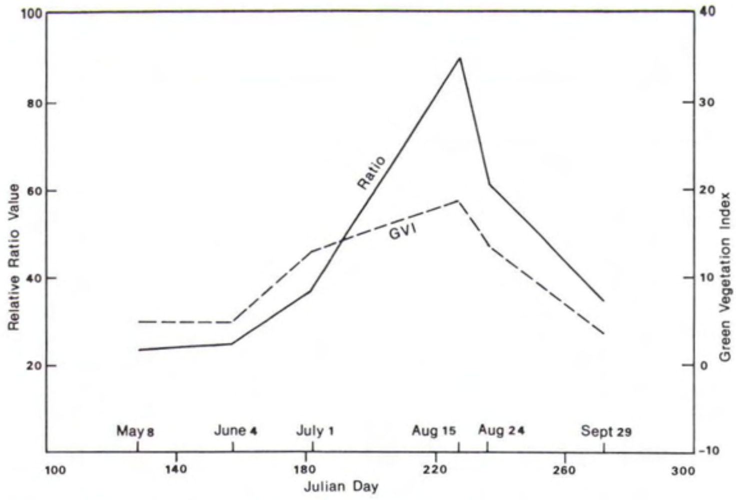

FIG. 2. Ratio and Green Vegetation Index temporal profiles of a corn sample pixel based on Landsat MSS data of the 1976 growing season. (The 1976 data are used in this particular figure to give a more complete comparison of the two profiles.)

the means'' (dnorm), which is the square of the absolute value of the difference between the mean pixel values of two sets divided by the sum of the variances of the two sets. It can be written as

$$\text{dnorm} = (u_1 - u_2)^2/(\delta_1 + \delta_2)$$

where the subscripts refer to the respective classes. This normalized distance is a measure of the statistical separability of the pattern classes. It is identical to that used in the University of Minnesota FINDSET program, which is a derivation of the NASA ERL SEARCH routine.

After some experimentation with the program, it was determined that the proper number of classes or clusters to be used was highly dependent on the type of data under analysis. For example, Green Vegetation Index data required more classes than did ratio data to achieve optimal classifications. Generally speaking, the number of classes required to produce the best results with any given set ranged from 30 to 50.

To assist in the analysis and identification of the large number of clusters, the mean of each cluster of the transformed data was used to construct temporal profiles of the various ground phenomena (Figure 3). The image analyst examined the profiles and grouped them into several land-use/land-cover pattern categories according to profile shape. This was done with the help of knowledge of the local crop calendar and the general characteristics of the spectral responses of the individual crop types across the growing season.

The second step in the unsupervised analysis was then to classify all pixels in the scene into the class to which they are nearest. For any single image the distance between a pixel and a class is computed by dividing the absolute value of the distance between the pixel value and the class mean by the standard deviation. For multiple images, the distance can be computed as

$$\sqrt{\frac{\sum_{i=1}^{n} [(\text{pixel} - \text{mean}) / \sigma]^2}{N}}$$

where N,n = number of images used in the classification, and
σ = class standard deviation.

It was on the basis of the above distance that all pixels in the multitemporal data set were assigned to the appropriate land-use/land-cover categories in our unsupervised analysis.

In addition to the unsupervised multitemporal analysis, we performed three other classifications for comparison purposes: (1) an unsupervised classification of image data from a single date (6 September), (2) a supervised classification of the multidate transformed data, and (3) a supervised classification of the same single date.

RESULTS EVALUATION

The classification results were compared to the aerial photographs taken on 6 September 1979 and the crop survey records of 28 July and 12 August of the same year. A total of 768 sample points (462 for study area II and 326 for study area I) were selected for this purpose. The number of sample points for each land-use/land-cover pattern category ranged

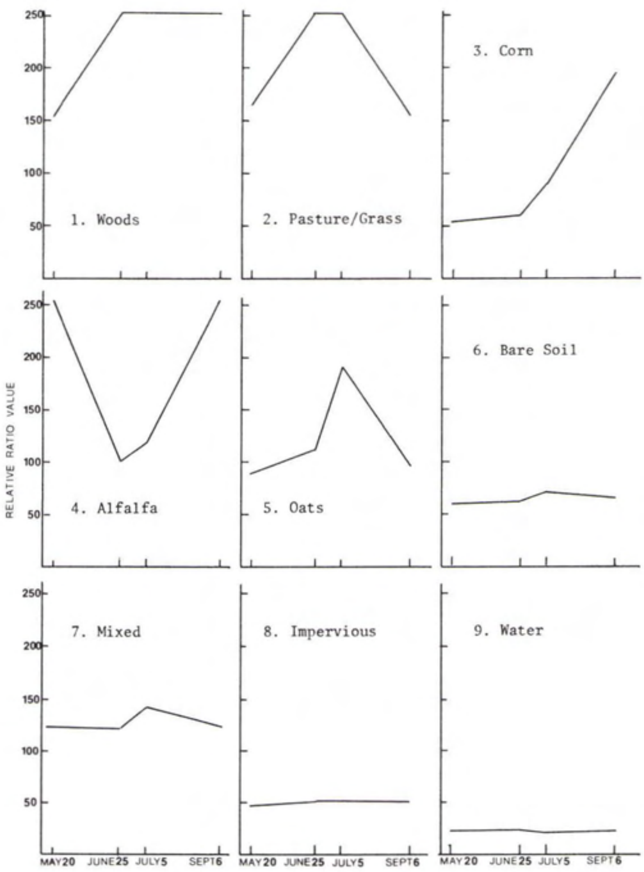

FIG. 3. The typical temporal profiles used for cluster grouping of 1979 data.

from 30 to 74. The sample points were interpreted manually with the help of the field survey records. Then the sample point coordinates were located on the various image classifications displayed on the STC color monitor. On the basis of these comparisons, we summarize below the best overall classification result obtained; the performance of multidate versus single date classification; the performance of supervised classification versus unsupervised classification; and the results obtained using ratio transformed data versus Green Vegetation Index transformed data.

THE BEST CLASSIFICATION RESULT

In terms of overall accuracy, the best result was produced by the unsupervised classification of the multitemporal M7/M5 ratio data (Plate 1). A total of nine land-use/land-cover categories resulted from this analysis (Table 1). They are woods, pasture/grass, corn, alfalfa, oats, bare soil, water, mixed, and impervious surfaces. Bare soil includes feed lots and fields with spotty vegetation. The mixed category includes pixels containing more than one ground cover. This category primarily represents residential areas, country roads, and farmsteads mixed with surrounding vegetation. The impervious surface category includes urban areas, major highways, shopping centers, and airport runways. Corn and alfalfa represent over half of the total area (30.8 percent and 26.0 percent, respectively). The pasture/grass category also constitutes a large share (18.9 percent) of the area. The overall accuracy of this classification is 89.8 percent, which is the summation of the accuracy of each class weighted by the number of pixels occurring in each class (Table 2).

The discrepancies between the reference data and the classification can be explained by one (or more) of the following: (1) inseparability of the temporal profile of certain resources; (2) misinterpretation and/or mislocation of the reference data sample points; and (3) misregistration of the multitemporal images.

The inseparability of the temporal profile of different land-use/land-cover pattern categories can be partially resolved by improving the temporal resolution of the data. This involves increasing the number and/or changing the timing of the dates of data used. Of course, the number and timing of

TABLE 1. UNSUPERVISED CLASSIFICATION RESULT OF THE TEMPORAL M7/M5 RATIO DATA OF STUDY AREA II.

Name	Number of Pixels	Area in Acres	Percentage of Total
Woods	5,468	6,015	5.2%
Pasture/Grass	19,490	21,439	18.9%
Corn	31,675	34,842	30.8%
Alfalfa	26,756	29,432	26.0%
Oats	592	651	0.6%
Bare Soil	4,488	4,937	4.4%
Water	1,496	1,646	1.5%
Mixed	12,407	13,648	12.1%
Impervious	501	550	0.5%
Total	102,873	113,160	100.0%

TABLE 2. AN ERROR MATRIX COMPARING GROUND REFERENCE AND THE UNSUPERVISED CLASSIFICATION RESULT OF TEMPORAL M7/M5 RATIO DATA OF STUDY AREA II.

CLASS		1	2	3	4	5	6	7	8	9	REFERENCE TOTAL
Woods	1	46	2		3						51
Pasture/Grass	2	4	59	1	6				2		72
Corn	3		1	72					1		74
Alfalfa	4		4	3	63				2		72
Oats	5			1	1	35	7				44
Bare soil	6		1				25			4	30
Water	7						2	35		1	38
Mixed	8		2		1				46	1	50
Impervious	9						5			26	31
Class. Total		50	69	77	74	35	39	35	51	32	462
Accuracy %		90.2	81.9	97.3	87.5	79.5	83.3	92.1	92.0	83.9	
Weighted Accuracy											89.8%

dates available is very much a function of the weather and satellite orbit and viewing parameters.

Another way of potentially improving the separability of the various cover types is to increase the number of clusters allowed in the unsupervised algorithm. There are, however, drawbacks and physical limitations to this process. It demands substantially more time of the image analyst to label clusters and, if too many clusters are used, some tend to represent artificial classes or noise as well as true ground classes of interest.

The misinterpretation of reference sample points and the mismatch of sample points between the ground references and imagery is always a possibility. Unfortunately, there is no good way for solving this problem except by repeating the procedure with another interpreter. Also, misrepresentation errors have the greatest influence in areas where fields are small and fragmented. The significance of this problem is reduced when the use of TM or SPOT satellite data is considered.

To further evaluate the accuracy of the classification, a visual examination of the entire classified image was made. This enabled the analyst to pinpoint misclassified boundary pixels, which cannot be accurately estimated by the sample point method. For example, some boundary pixels between water and land were classified as bare soil because the mixing of forested areas or pasture/grass with water generates a temporal profile corresponding to that of soil. It is estimated that about 3 to 5 percent of the pixels were misclassified because of this effect. Accounting for these types of boundary pixel errors and other observable pure pixel errors, it is estimated that this classification has an accuracy level of 84 to 86 percent. This is considered quite encouraging in light of the fact that, for most of the critical period for crop discrimination (part of July and all of August), no data were available for our analysis. If data were available for this period, we believe the accuracy would be even further improved.

MULTI-DATE VERSUS SINGLE DATE CLASSIFICATION

Again, in order to compare the usefulness of the multidate data with that of single date data, the September scene was classified by means of the same unsupervised algorithm. The classification results (66 percent) are quite inferior to those obtained with the temporal ratio data (Plate 2).

To label the single date classification, clusters were recognized by comparing their distribution with the reference data—in this case, the aerial photographs. Without the information on temporal profiles of the clusters, the process was tedious and time-consuming and some clusters contained pixels from several land resource categories. Twenty-four cluster nuclei were employed in this classification. However, four clusters dominated the scene and the analyst was forced to assign them to the major land-cover categories. It is suspected that it might have been possible to refine the clusters by increasing the number of nuclei to 40 or more. It became impractical, however, to attempt to label so many clusters. More importantly, certain feature types simply were not spectrally separable in this single date imagery. For example, the spectral reflectance of woods is identical with that of corn at this time period; hence, 30 out of 51 woods category pixels were assigned in error to the corn category.

Supervised Versus Unsupervised Classification

Using a supervised classifier, training data are required to provide statistical representation for the entire population. Normally, knowledge of selecting training data is based on the visual interpretation of the raw Landsat image, reference to ground survey records, and/or reference to aerial photographs collected at approximately the same time as the imagery. When classifying multitemporal agricultural scenes, visual interpretation of one Landsat image or supplementary information collected at one point of time is far from ideal for selecting training samples. Training samples selected in this way will often result in some misrepresentation, with the amount of error dependent on the particular land-use/land-cover category, the date of the data used, and the particular growing conditions.

To remedy the above problem, we selected training sets in two steps. Training area polygon coordinates were first taken from the 6 September data. The polygon coordinates which registered on the bit plane of the STC were saved and later remapped onto the M7/M5 ratio temporal data which were loaded into the three display channels. On the basis of the color rendition of the different ground covers, the analyst was able, to some extent, to recheck the correctness of the training data. The final classification result (83.1 percent), was similar to, but not as good as, the classification generated by the unsupervised method (Plate 3).

In order to compare the performance of single date data using the maximum likelihood routine, the same set of training data were applied to the 6 September 1979 data. The accuracy (72.8 percent), is far below that obtained with the temporal data (Plate 4). Nevertheless, this result is better than that obtained with unsupervised classification of the single date data.

As mentioned previously, training data selection is a Herculean task for multitemporal analysis. Of course, one can construct temporal profiles using the means of n-dimensions of the training sets for verification. The point is that there is always significant duplication of information in this process, and it is virtually impossible to exhaust all the variations of the shapes of temporal profiles existing in the data. It is an arduous experience for the analyst to go back to the beginning of the process frequently to take training polygons for the "missing pieces of the puzzle."

Ratioed Data Versus Green Vegetation Index Data

The Green Vegetation Index, which is sensitive to the vigor of vegetation, is the result of linear transformation of all four bands of MSS data. Therefore, in theory, GVI contains more information and gives a better portrait of the ground vegetation than do the ratio data for two bands. Visual comparison of the two types of transformed data tends to confirm this judgement. The images of GVI demonstrate greater variation of medium grey tones within fields and between fields than do those of ratio data, which tend to polarize toward either black or white.

Surprisingly, the richness of information of GVI data created difficulties for the unsupervised classifier. A larger number of clusters were required to classify the data, and considerably longer time was needed to group and label the clusters (Plate 5). It is speculated that the above problem was due to the use of four bands, especially band 4. Some information that was included is considered to have been noise under the unsupervised classification scheme used. Comparing the classification results of both ratio and GVI transformed data (85.7 percent and 83.9 percent, respectively), the number of pixels assigned to the various land-use/land-cover pattern categories is very similar (Table 3).

CONCLUSION

Two schools of thought regarding the processing of multitemporal data are recognized. One advocates the use of conventional classification techniques, the other advocates the use of a graphical shape matching procedure called "profile technology."

The technique described in this paper is intended to combine the best of both approaches—to merge the unsupervised classification technique and the temporal profile concept. This offers a new approach for classifying transformed multitemporal remote sensing data which appears to be particularly suited to agricultural land-use/land-cover mapping. The method is simple and the results obtained are better than those obtained in comparable single-date and supervised analyses. One might argue that 84 percent to 86 percent accuracy is not adequate

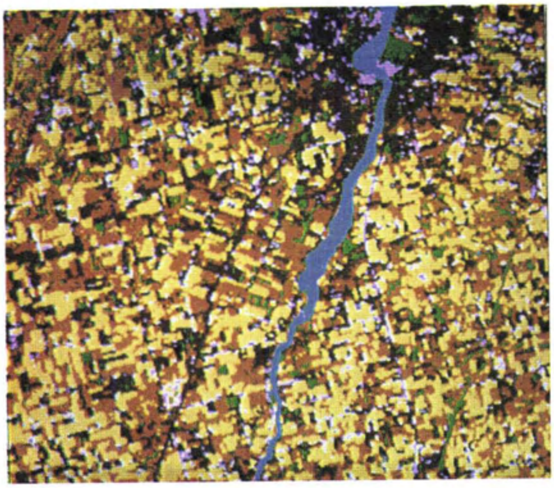

PLATE 1. Unsupervised classification result of Landsat MSS ratio transformed temporal data of study area II.

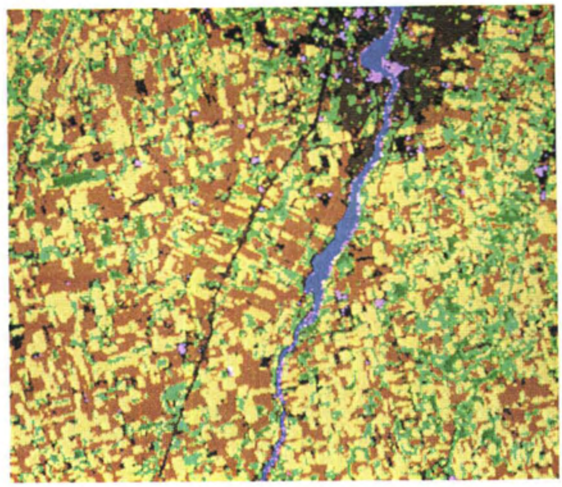

PLATE 2. Unsupervised classification result of single date Landsat MSS data (6 September 1979) of study area II.

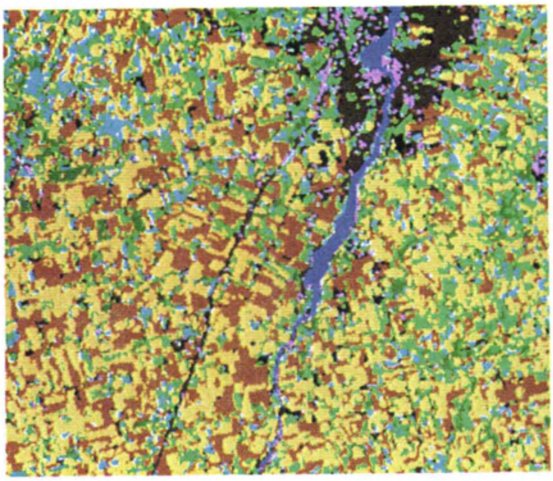

PLATE 3. Supervised classification result of Landsat MSS ratio transformed temporal data of study area II.

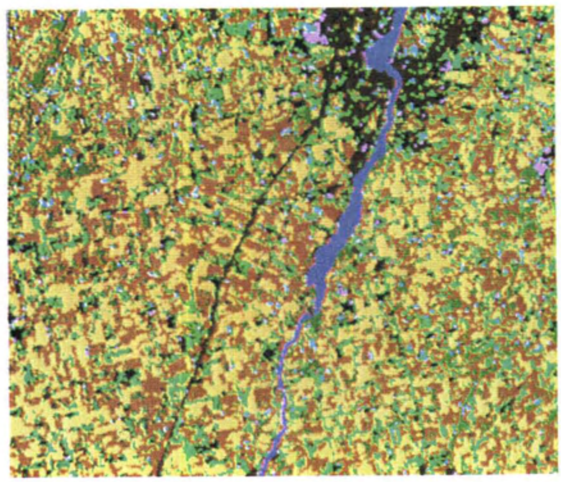

PLATE 4. Supervised classification result of single date Landsat MSS data (6 September 1979) of study area II.

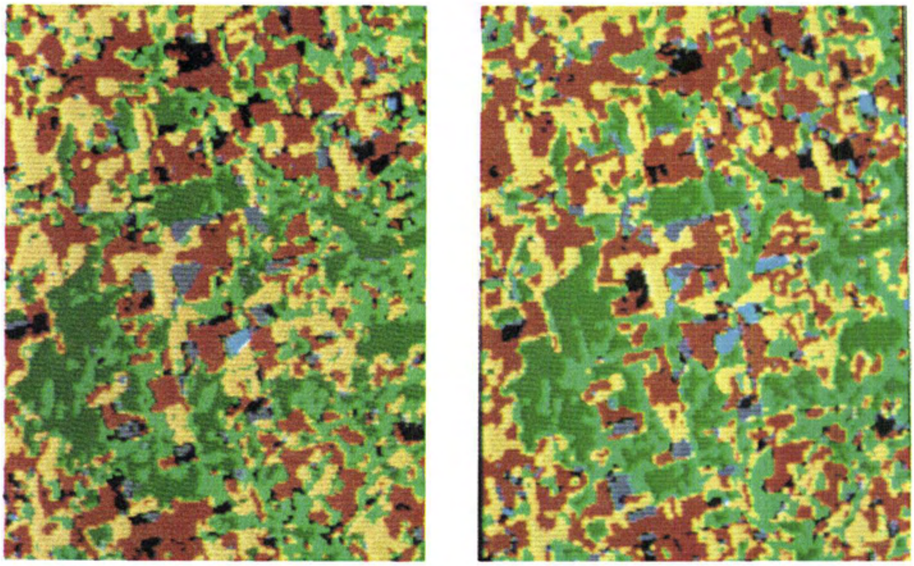

PLATE 5. Unsupervised classification results of Green Vegetation Index transformed temporal data (left) and ratio transformed temporal data (right) of study area I.

TABLE 3. A COMPARISON OF UNSUPERVISED CLASSIFICATION RESULTS OF M7/M5 RATIO AND GVI TRANSFORMED DATA OF STUDY AREA I.

	Ratio Dates		GVI Transformed Data	
Name	Number of Pixels	Percentage of Total	Number of Pixels	Percentage of Total
Woods	5,232	16.0%	5,335	16.3%
Pasture/Grass	7,378	22.6%	7,814	23.9%
Corn	10,129	30.9%	9,042	27.7%
Alfalfa	6,218	19.0%	6,524	19.9%
Oats	1,711	5.3%	1,415	4.3%
Bare Soil	1,861	5.7%	2,500	7.7%
Unknown	176	0.5%	75	0.2%
Total	32,705	100.0%	32,705	100.0%

for some applications. We would like to reiterate that in this investigation we employed only four dates of data, and no data were available for the most critical part of the growing season. With the improvement of the temporal, spatial, spectral, and radiometric resolution of other data (such as TM and SPOT) and their improved geometric fidelity, the accuracy of this method will likely improve substantially.

REFERENCES

Abotteen, R.A., 1977. Principal component greenness transformation in multitemporal agricultural Landsat data. *Proc., 11th Int'l Symp. on Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 765–774.

Badhwar, G.D., J.G. Carnes, and W.W. Austin, 1982. Use of Landsat-derived temporal profile for corn-soybean feature extraction and classification. *Remote Sensing of Environment*, Vol. 12, pp. 57–59.

Bauer, M.E., J.E. Cipra, Paul E. Anuta, and J.A. Etheridge, 1979. Analysis of agricultural crops by computer classification of Landsat MSS data. *Remote Sensing of Environment*, Vol. 8, pp. 75–92.

Bizzell, R.M., F.G. Hall, A.H. Feiveson, M.E. Bauer, B.J. Davis, W.A. Malila, and P.C. Rice, 1975. Results from the crop identification technology assessment for remote sensing (CITARS) projects. *Proc., 10th Int'l Symp. on Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 1189–1198.

Bodner, M.S., 1979. Separation of various small grain Lacie spectral signatures using time evolution patterns of householder transformation generating functions. *Remote Sensing Quarterly*, Vol. 1, No. 1, pp. 6–17.

Chandrasekhar, S., and M. Maruthachalam, 1978. Analysis on multi-data Landsat data. *Proc., 12th Int'l Symp. on Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 1769–1777.

Crist, E.P., and W.A. Malila, 1980. A temporal-spectral analysis technique for vegetation application of Landsat. *Proc., 14th Int'l Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 1031–1121.

———, 1981. A technique for automatic labeling of Landsat agricultural scene elements by analysis of temporal-spectral patterns. *Proc., 15th Int'l. Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 1227–1236.

Dana, Robert W., 1978. Using airborne radiometry to determine atmospheric effects on Landsat data. *Proc. ASP, Fall Technical Meeting*, Albuquerque, New Mexico, pp. 117–129.

Dawbin, K.W., and T.D. Beach, 1981. Crop monitoring in Australia using digital analysis of Landsat data. *Proc. Machine Processing of Remotely Sensed Data Symp.*, LARS, Purdue U., W. Lafayette, Ind., pp. 76–79.

Engvall, J.L., J.D. Tubbs, and Q.A. Holmes, 1977. Pattern recognition of Landsat data based upon temporal trend analysis. *Rem. Sens. of Environ.*, Vol. 6, pp. 303–314.

Hixson, M.M., M.E. Bauer, and D.K. Scholz, 1980. An assessment of Landsat data acquisition history on identification and aerial estimation of corn and soybeans. *Proc., Machine Processing of Remotely Sensed Data Symp.*, LARS, Purdue U., W. Lafayette, Ind., pp. 72–77.

Kauth, R.J., and G.S. Thomas, 1976. The tasseled cap - a graphical description of the spectral-temporal development of agricultural crops as seen by Landsat. *Proc., Machine Processing of Remotely Sensed Data Symp.*, LARS, Purdue U., W. Lafayette, Ind., pp. 4B-41–4B-51.

Lachowsky, H.M., and F.Y. Borden, 1973. Classification of ERTS-1 MSS data by canonical analysis. *Symposium on Significant Results Obtained from ERTS-1*, Vol. 1, Section B, pp. 1243–1251.

Malila, William A., Peter F. Lambeck, and Eric Crist, 1980. Landsat features for agricultural applications. *Proc., 14th Int'l Symp. on Rem. Sens. of Environ.*, Research Inst. of Michigan, Ann Arbor, pp. 793–803.

Merembeck, B.F., and F.Y. Borden, 1978. Principal components and canonical analysis of reduction of the dimensionality of large data sets. ORSER technical rept. 5-78, Office for Rem. Sens. of Earth Resources, The Penn. State U., Univ. Park, Pa.

Merembeck, B.F., and B.J. Turner, 1979. Directed canonical analysis and the performance of classifiers under its associated linear transformation. *Proc., Machine Processing of Remotely Sensed Data Symp.*, LARS, Purdue U., W. Lafayette, Ind., pp. 314–322.

Mergerson, James W., 1981. Crop area estimates using ground-gathered and Landsat data—a multitemporal approach. *Proc., 15th Int'l Symp. on Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 1211–1218.

Misra, P.N., and S.G. Wheeler, 1977. Landsat data from agricultural sites: crop signature analysis. *Proc., 11th Int'l Symp. on Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 1473–1482.

———, 1978. Crop classification with Landsat multispectral scanner data. *Pattern Recognition*, Vol. 10, pp. 1–13.

Richardson, A.J., and C.L. Wiegand, 1977. Distinguishing vegetation from soil background information. *Photogrammetric Engineering and Remote Sensing*, Vol. 43, No. 12, pp. 1541–1552.

Robinove, C.J., 1982. Computation with physical values from Landsat digital data. *Photogrammetric Engineering and Remote Sensing*, Vol. 48, No. 5, pp. 781–784.

Rogers, R.H., K. Peacock, and Navinchandra J. Shah, 1973. A technique for correcting ERTS data for solar and atmospheric effect. *Symp. on Significant Results Obtained from ERTS-1*, NASA, New Carrolton, Md. Vol. 1, SecB, pp. 1115–1122.

Scarpace, F.L., K.W. Holmquist, and L.T. Fisher, 1978. Landsat analysis of lake quality for statewide lake classification. *Proc., 44th ASP Annual Meeting*, Washington, D.C., pp. 173–195.

Tanaka Sotaro, *et al.*, 1978. Multi-seasonal data analysis some extensions for environmental monitoring. *Proc., 12th Int'l Symp. on Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 909–918.

Tubbs, J.D., 1980. Classification of Landsat multitemporal training data based upon growth curve analysis. *Proc., 14th Int'l Symp. on Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 1123–1127.

Turner, Robert E., 1978. Elimination of atmosphere effects from remote sensing data. *Proc. 12th Int'l Symp. on Rem. Sens. of Environ.*, Environ. Research Inst. of Michigan, Ann Arbor, pp. 1123–1127.

Wall, S.L., R.W. Thomas and L.R. Tinney, 1979. Landsat based multi-phase estimation of California's irrigated lands. *Proc., ASP-ACSM Fall Technical Meeting*, Sioux Falls, SD, pp. 221–236.

Wheeler, S.G. and P.N. Misra, 1980. Crop classification with Landsat multispectral scanner data II. *Pattern Recognition*, Vol. 12, pp. 219–228.

Woolford, T.L., 1983. A mathematical model for crop spectral-temporal trajectories based on a plant growth model. *Proc., Machine Processing of Remotely Sensed Data Symp.*, LARS, Purdue U., W. Lafayette, Ind., pp. 208–215.

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