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Assessment of TM thermal infrared band contribution in land cover/land use multispectral classification

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ABSTRACT: Thermal data from Landsat 4 TM were used in conjunction with the six reflective TM bands to assess the contribution of the thermal band in eight multispectral classifications using four different data sets. Despite its coarse resolution and differences in radiometric measurements, the thermal data provided an additional informational plane in the generation of Principal Components. This informational plane did not appear when the thermal band was excluded from the linear transformation. The use of all seven TM bands for cluster statistics generation provided greater statistically separability between pairs of spectral classes than when only reflective bands were used. Classification with subsets of selected bands gave better results than classification performed without the use of the thermal band for statistics generation. Classifications with Principal Components reduced the number of spectrally separable classes, but with a significant reduction in computer time.
The present paper is an abbreviated version of a Master of Science thesis (Valdés, 1984), as part of the LIQDA NASA contract NAS5-26859 conducted by LARS/Purdue University.

1 INTRODUCTION

Thematic Mapper sensor era started with the launch of Landsat 4, the first of the second generation of Landsat satellites. This sensor has better spatial resolution than the earlier Multispectral Scanner onboard Landsats 1,2 & 3 (30 m -vs- 80m), seven spectral bands instead of four, and four the number of quantization levels (256 -vs- 64).

The T.M. also has a band in the thermal infrared region of the spectrum, this band differs from the reflective bands in its spatial resolution (120 m) and the type of electromagnetic measurements. This band has not been used often by the scientific community either in the experiments with T.M. simulators or in the first analysis conducted by NASA on the Landsat Image Data Quality Analysis.

The hypothesis of this study is that the use of the T.M. thermal infreres band in conjunction with the six reflective bands will provide better discrimination of agricultural and urban features than does classifications with the six reflective bands only. The hypothesis can be expressed as:

Ho = P(7 TM bands) $>$ P(6 TM reflective bands)

H1 = P(7 TM bands) $\leq$ P(6 TM reflective bands)

Where P = goodness of classification.

Principal Components analysis (data compression technique) was also performed to evaluate the contribution of each band to the informational content of the T.M. data.

2 LITERATURE REVIEW

2.1 Agricultural mapping with remote sensing data

The specialized literaure in remote sensing contains many examples of the detection and quantification of crops using techniques of digital analysis. Many of these applications are considered either experimental systems (Bauer, et al.,1971;Bauer, 1977; Valdés,1981) or quasi-operational systems (McDonald and Hall,1978)

The results of some of these experiments show different degrees of accuracy in the identification and quantification of crop resources. However, all these results demonstrate a great potential for surveying crops due to the characteristics of the data obtained by the Landsat sensors, and the computer processing, for monitoring the vegetative resources in large geographic areas.

There is a great amount of documentation available related to the physiological, physical and spectral behavior of vegetation. These must be considered in understanding how solar energy interacts with the vegetation and in order to interpret data from multispectral sensors.

In 1963, Hoffer and Johannsen working with different vegetative species (corn, soybeans and 3 timber species), found that the spectral response of all those species have the same typical vegetation curve. They also found significant differences in the response -- at certain wavelengths, mainly in the visible and near infrared portions of the spectrum.

To discriminate crop species by means of remote sensing, several factors related to the cultural practices for each crop must be considered, such as plant and row spacing, geometric arrangement of the plants, fertilization and irrigation practices, and growth cycles. The differences in reflectance wich allows us to discriminate between vegetative species, are due to the characteristics of the leaves and canopies of different species. All these internal and external factors influence the optical properties of the leves and canopies. The spectral patterns sensed by the scanners represent the integration of all of them.

2.2 Thermal and environmental effects of incoming solar energy

In order to interpret remote sensing data of vegetation, it is important to comprehend the interaction of the plant with its environment. A plant is exposed to electromagnetic radiation from its surroundings, such as soil, rocks, plants, sun, sky, clouds and atmosphere. All objects above absolute zero radite energy by virtue of their tempreature and emittance. At temperatures normally exhibited by objects at or near the earths surface, this radiation is almost entirely in the infrared wavelength region from 4 um to 100 um approximately (Swain and Davis, 1978).

Plants in stress caused by insects, diseases, physiological disorders, nutrient deficiency and adverse environmental effects suffer detectable temperature and or emittance changes (Kumar and Silva, 1973).

Several authors have presented the potential use of thermal change detection on plants in order to evaluate stress causal agents. Clum (1926) and Curtis (1936) related soil moisture stress with temperature differences in cotton and potatoes. Wear (1966) found an increase in temperature in forest trees with roots damaged by insects. Myers and Allen (1968) realted soil salinity with high cotton leaf temperatures.

The Corn Blight Watch Experiment, demonstrated that use of infrared remote sensing has possitive effects in stress levels determinations (MacDonald, et al., 1972; Kumar and Silva, 1973).

2.3 Airbone multispectral scanning thermography

Myers, et al. (1966) made use of pictorial and thermal infrared data to determine differences in the temperature of plants as an indicator of the relative subsurface salinity and moisture conditions affecting crop production. They stated that the temperature contrasts between salt affected and unaffected cotton plants are likely to be greater than the temperature contrasts between moisture stressed and unstressed cotton.

Wiegand, et al. (1968), using the UNiversity of Michigan airborne thermal scanner in Texas, studied the thermal behavior of several variables such as crop species, plant spacing, tillage, irrigation regime and special features, such as highways and water reservoirs.

They found that irrigated crops tend to be cooler that non irrigated at midday conditions, but the opposite results were obtained at early morning hours. Thermal differences related to tillage were minimal.

The feasibility of using thermal imagery for land use land cover studies has been demonstrated. Brown and Holz (1976) following Anderson´s classification system (Anderson, et al.,1976), produced a land use/land cover map of Oak Creek Lake, West Texas.

2.4 Thermal band of Landsat 3

The Landsat 3 MSS characteristics are in sense the same as those of the previous Landsats, except that Landsat 3 acquired additional data in the thermal infrared portion of the spectrum (10.4 to 12.6 um) with a ground resolution of 237 m. As a result, a single thermal band measurements corresponds to an area represented by nine measurements in each of the four reflective spectral bands, a 9 to 1 ratio (Price, 1981).

The Landsat 3 thermal band did not function properly due to several unexpected causes. The problems associated with the thermal sensing system were reflected in the quality of the imagery. Both thermal and spatial resolution were affected and the thermal imaging system was eventually turned off in the spring of 1979 (Price,1981; Lougeay,1982).

Despite the problems associated with the thermal band, some analysis was performed to evaluate the contribution and usefullness of this band. Price (1981), using Principal Components analysis, assessed the statistical correlation between the emissive band, and the four reflective bands. He found that the thermal data either were not useful or were associated with a physical parameter that is not directly related to surface type. He found that thermal data made a limited contribution to multispectral classifications. He concluded that its use for classification is subject to ambiguities and prone to error: "...an indiscrimante use of the thermal data appears to be undesirable because of many possibilities for misinterpretation and the fact that the thermal 'signature' is not a direct indicator of surface type."

Lougeay (1982) compared the Landsat 3 MSS band 5 (0.6 to 0.7 um) and the thermal MSS band 8 (10.4 to 12.6 um). He found the thermal imagery of MSS band 8 to be of limited use by itself due to its coarse spatial and thermal resolution. However it did provide a rendition of gross topographic structure which was not readily available from the other MSS spectral bands.

2.5 Classifiaction and data compression techniqes

If the use of all available channels was not possible, data compression techniqes have been used to represent the large content of data into fewer components.

Principal Components or Karhunem - Loeve transformation is an orthogonal linear transformation that compresses multidimensional data into fewer dimensions without significant loss of information content. This transformation assigns the random variance or noise to eigenvectors with lowest variance (Bartolucci, et al., 1983).

Data compression is one result of the generation of principal components. It is possible to describe the relative influence or "pull" of the original ban-s on each of the new components. This procedure allows us to evaluate which of the original bands contains most of the significant variance or information content for a particular data set (ANuta, et al., 1984)

3 METHODOLOGY

3.1 Landsat TM characteristics

The TM data utilized to carry out the present project were gathered by Landsat 4 on 3 September 1982 over the central Iowa. The NASA scene number is 40049-16[illegible] accesion 182, path 27, row 31. The TM data used was radiometrically and geometrically corrected, i.e., P-tape or fully processed tape, and consisted of 5,[illegible] scan lines with 6,976 pixels per line. The geometric correction of the TM thermal data requires special consideration, since the spatial resolution of thermal data is 129 m compared to 30 m for the other TM bands. One image sample or pixel of raw thermal data represents an area equivalent to 16 area units from any of the reflective bands. The coarse resolution of the thermal data is resampled to forma a registered grid of 28.5 m by 28.5 m pixels. Thus all bands of the geometrically corrected TM data contain the same number of pixels per unit area.

3.2 Description of the study area

A study area of 10 by 10 sections (approximatelly 26,000 hectares), was selected as representative of a great diversity of land use/land cover features. This area is located in Polk County which is in south central Iowa.

The area lies between latitudes 41°37'45" N and 41°46'15" N, and from longitude 93°37' W to 93°45' W. The general topography is nearly level to undulating with some steep areas along the streams and rivers. The geology of the area consists mainly of a Wisconsonian glacial till. The entire area is underlain by a shale bedrock of the Des Moines Group.

The native vegetation of Polk County was praire grasses and hardwood forests. The forests grew along the major streams, particularly along the Des Moines River. The cover types in this area are water bodies, agricultural fields, urban areas (new and old developments) industrial and commercial parks, and a dense road network (from gravel roads to four lane highways).

The Agricultural Stabilization and Conservation Service (ASCS) of the US Department of Agriculture in Polk County collected 35 mm color aerial slides for the entire county in August 1982. Each slide covers two sections (approximately 520 ha) on the ground. These slides were used in conjunction with aerial infrared slides obtained by the Laboratory for Applications of Remote Sensing (LARS) of Purdue University in May 1983 over selected sites in the county as reference data.

The hardware and software used for the present researcg resided at LARS/Purdue U. The software system for digital analysis of multispectral data is LARSYS (Phillips, 1973) and LARSYSDV (Mrcoczynski,1980).

3.3 Study data sets

Four data sets of the classified area were used to evaluate the contribution of the thermal data in the multispectral classifiaction. The first data set is the original seven TM bands. The second set is composed of the same original TM bands excluding the thermal band. The third data set is formed by Principal Components loaded from the original seven TM bands. The fourthdata set is also Princiapl Components, but generated from the second data set, i.e., only the reflective bands.

The satistics used in calculating the Principal Components were generated from data samples of the original TM data set using every fifth line and fifth column.

Tables 1 and 2 show the statistics for both Principal Components data sets. Tables 3 and 4 list the eigenvales and the corresponding amount of data variance taht is accounted for by their respective eigenvectors for both data sets.

3.4 Spectral analysis procedure

A non-supervised approach (Clustering) was selected to generate the training statistics. This approach groups spectrally similar pixels regardles of their spatial position (Tilton and Bartolucci, 1982). and extracts the maximum quantity of information available in the TM data.

Eight classifications were carried out in this study. Only four spectral analysis were conducted, one for each of the data sets, the classifications are results of different channel combinations selected after the analysis procedure (Table 5).

To avoid analysis bias in the generation of training statistics, the same eight training areas and number of cluster classes were requested for each of the four data sets.

The analysis was performed utilizing a defined threshold of 1850 for the transformed divergence distance (D.T.),(Swain and Davis, 1982).

Table 1. Eigenvector values for by their respective TM band for the original seven TM bands (Data set C).

	Wavelength Band	Principal Component (Karhunen & Loeve) Eigenvector 1	2	3	4	5	6	7
	1	0.0376	0.4331	0.5665	-0.1086	-0.1359	-0.6781	-0.0092
2	2	0.0377	0.2641	0.2770	-0.0547	-0.1632	0.4311	0.7988
3	3	0.0293	0.4032	0.3564	-0'0806	-0.0598	0.5898	-0.5930
4	4	0.8109	-0.4312	0.3666	0.0817	0.1167	0.0396	-0.0163
5	5	0.5574	0.4391	-0'5642	-0.0719	-0.4097	-0.0659	-0.0275
7	7	0.1670	0.4115	-0.1578	-0.0465	0.8770	-0.0210	0.0961
6	6	-0.0101	0.1830	0.0285	0.9822	-0.0272	-0.0116	-0.0013

Table 2. Eigenvector values for by their respective TM band for the six reflective TM bands (Data set D).

Wavelength Band	Principal Component (Karhunen & LOeve) Eigenvector 1	2	3	4	5	6
1	0.0393	0.4400	0.5694	-0.1389	-0.6792	-0.0092
2	0.0388	0.2654	0.2787	-0.1646	0.4307	0.7986
3	0.0309	0.4096	0.3590	-0.0619	0.5888	-0.5932
4	0.8093	-0.4434	0.3638	0.1190	0.0405	-0.0162
5	0.5591	0.4440	-0.5619	-0.4115	-0.0666	-0.0275
7	0.1686	0.4177	-0.1454	0.8754	-0.0220	0.0960

Table 3. Eigenvalue and the corresponding amount of variance that is accounted for by their respective eigenvector for the data set C.

Eigenvector	Eigenvalue	Percent Variance	Cumulative Percent Variance
1	795.642	54.449	54.449
2	554.802	37.967	92.416
3	81.346	5.567	97.983
4	14.888	1.019	99.002
5	10.281	0.704	99.706
6	2.818	0.193	99.899
7	1.482	0.101	100.000

Table 4. Eigenvalue and the corresponding amount of variance that is accounted for by their respective eigenvector for the data set D.

Eigenvector	Eigenvalue	Percent Variance	Cumulative Percent Variance
1	795.569	55.706	55.706
2	536.714	37.581	93.287
3	81.290	5.692	98.979
4	10.285	0.720	99.699
5	2.820	0;197	99.896
6	1.482	0.104	100.000

Table 5. Study data sets used for multispectral analysis and the eight different classification approaches.

Data Set	Classif. Approach	Statistics Generation	Classification Bands
A	I	7 TM bands	7
A	II	7 TM bands	6 reflective
A	III	7 TM bands	6 best
A	IV	7 TM bands	4 best
B	V	6 reflective	6
C	VI	4 Princ. Comp.	4
C	VII	4 Princ. Comp.	3 best
D	VIII	3 Princ. Comp.	3

If a pair of classes had a value of DT of 1850 or greater, these classes were considered different and spectrally separable. Then the analysis was focused on those with DT values less than 1850.
Final cluster classes selected to train the computer for classification are those which were considered totally discriminable within the cluster classes and representative of the land cover/land use features present in the study set. The cluster classes that were not used for classification were "deleted" from the stattistics deck.
The multispectral classifiaction was performed using a "Per - Point" Maximum Likelihood Classifier.

4 RESULTS

4.1 Principal Components evaluation

To evaluate the importance of the thermal band for classification purposes, two Principal Components transformations were performed, one utilizing the seven original TM bands and other with the six reflective bands. The coefficients of the high ordered Principal Components describe which of the TM bands contains most of the significant variance of information for this data set.
The fourth Principal Component was almost entirely loaded with the thermal band (98.22%) and accounts for 1.019 % of the scenen variation. This result show that the thermal band is highly correlated with the fourth Principal Component (Table 1) as first reported by Bartolucci, et al.,1983. Even though the thermal data provided only one percent of the total scene variation, (Table 3), thermal information or variance may be distinctly unique from the rest of the bands.
The use of the thermal band in linear transformations of TM data creates a fourth dimension or Principal Component which is highly correlated with the thermal band (Table 1). This plane or Fourth Principal Component does not appears in the transformation performed using the six reflective TM bands only (Table 2).
Figures 1 and 2 show graphically the loadings or coefficients for both principal components data sets. Principal Components 1, 2, and 3 of both data sets had more or less the same shape as did the last three Principal Components of both data sets.
The results of the linear transformaton performed in the data set B containing the six reflective TM bands were compared with the results obtained by Crist and Cicone (1984) with a scene over North Carolina. They did not use the thermal band for the "Tasseled Cap Transformation". The found that with six TM reflective bands there are only three components or features. If the thermal band is employed in the transformation, the result will be four planes of information in which the use of a fourth component will account for

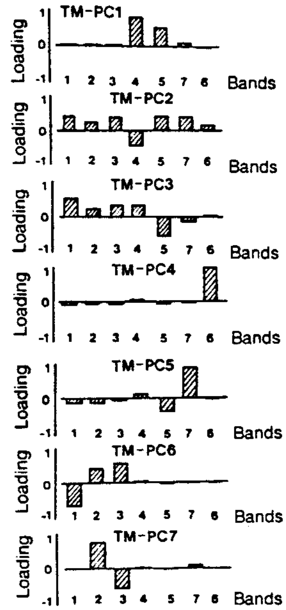

Figure 1. Loadings or coefficients for Principal Components of original 7 TM bands (Data set C).

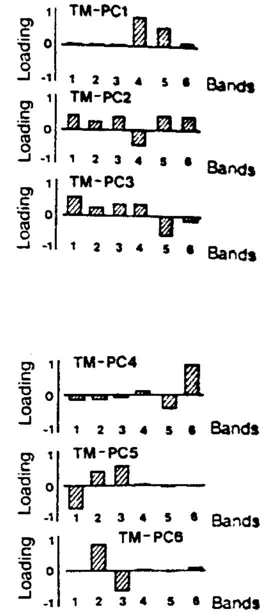

Figure 2. Loadings or coefficients for Principal Components of 6 reflective TM bands. (Data set D).

over 99 % of the cumulative data variation.
Considering that MSS data have two main Principal Components (Anuta, et al.,1984) or Tasseled Cap Planes and that TM data have four features of data when the thermal band is considered in the transformation; then the uncorrelated planes of data provided by the TM can be considered twice that those obtained with MSS data. This results agrees with the results of Anuta, et al. (1984), where they obtained 42 spectrally separable classes with TM data and only 21 spectrally separably classeswith MSS data from the same area.

4.2 Classifiaction with all available bands (Approach I)

The multispectral analysis performed in the first data set produced 37 spectrally separable classes. The classes selected for classification were considered the most representative of the scene variation from all the spectral cluster classes obtained.
This type of classification is the standard procedure when there are no constrains in computational facilities (Anuta, et al., 1984).

4.3 Classifiaction with six reflective TM bands (Approach II)

This approach was performed to compare the classification results with the first classification. In this approach the thermal band was not included in the Per Point classification, but the training classes selected were generated with the inclusion of that band.

4.4 Classifiaction with the best six TM bands (Approach III)

To evaluate the possible changes in classifiaction for the second approach, a classification with the best 6 bands (Bands 1, 3, 4, 5, 6 & 7) was performed to assess the effect of elimination of a single band on classification.

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4.5 Classification with the best four TM bands (Approach IV)

A classification with the best four bands was performed to compare this results with those of four Principal Components. Even though the combination of bands 1, 4, 5, and 6 had a greater average DT (1975 -vs- 1973); the 1, 4, 5 and 7 band combination was selected because of the higher minimum DT value obtained with this combination (660 -vs- 457).
These results confirm that band 7 provides more information in the higher ordered Principal Components transformation than does the thermal band.

4.6 Classification with the six reflective bands (approach V)

If digital pattern recognition analysis of remotely sensed data is performed with a selected combinatio- of spectral bands the training statistics (cluster) must be generated with those bands (Swain, 1983).
A second multispectral analysis was conducted over the same area to evaluate a classification performed without the thermal band. The training stattistics were derived from the six reflective bands only.
There were 37 spectrally separable classes as in the data set A, but there were differences between the training statistics of the two data sets. This second set of training statistics had more mixed spectral classes than did the data set A. This mixing occured mainly in non-water, non-vegetative classes. Both the minimum and the average DT values for the second data set (B) were greater than those obtained in the data set A.

4.7 Classification with 4 Principal Components (Approach VI)

The multispectral analysis of Principal Components was carried out with a slightly different technique than that used for the analysis of the TM bands. The selection criteria used in the analysis of Principal Components was based mainly on the separability betweeen pairs of classes and their spatial distribution on the cluster map.
The final training statistics for approach VI contained 35 spectrally separable classes. However, the number of mixed spectral classes had increased. The minimum and average separability values were greater in approach VI than those obtained using the best four bands (approach IV).

4.8 Classification with 3 Principal Components (Approach VII)

The first three principal components of data sets C and D contained approximately the same amount of information, the difference being that the data set D had slightly greater cumulative percentage variance than did the data set C (Tables 3 and 4). A classification with the first three Principal Components of data set C was performed to be compared with the classification from data set D.

4.9 Multispectral analysis of data set D (Approach VIII)

In data set D the first three principal components account for 98.979 % of the total variance in the scene (Table 4). These three components were utilized in the multispectral analysis, in which 31 spectrally separable classes were obtained.
The minimum DT value obtained in this approach was significantly greater tahn that obtained in the data set C for the best (first) three Principal Components (Approach VII). There was no great difference among the average separability of all the eight approaches.

Table 6. Average and minimum separability values (Transformed Divergence Distance, DT) for each classifiaction approach.

Approach	Bands or P. Components	Minimum Separability	Average Separability
Data set A = 37 spectrally separable classes			
I	1,2,3,4,5,6,7	1625	1991
II	1,2,3,4,5,7	959	1983
III	1.3.4.5.6.7	1578	1990
IV	1,4,5,7	660	1973
--	1,4,5,6	457	1975
Data set B = 37 spectrally separable classes			
V	1,2,3,4,5,7	1659	1991
Data set C = 35 spectrally separable classes			
VI	1,2,3,4	1650	1986
VII	1,2,3	753	1970
Data set D = 31 spectrally separable classes			
VIII	1,2,3	1534	1979

4.10 Visual evaluation

The eight classifiactions were displayed on a color video display device where they were visually evaluated. This evaluation was performed by assigning a different color for each of the spectral classes obtained in the 8 classifications and comparing them with the low altitude aerial photographs.
The classifiactions performed with the data set A, were considered the best. THe classifications performed with data sets B, C and D were ranked from good to bad in that order.

4.11 Statistical evaluation

To evaluate the classification accuracy of each approach, the final spectral classes obtained for each data set were grouped into nine major domains: Corn, soybean, forest, grass, bare soil, roads, urban, industry and water. One hundred pixels of known identity were defined for each of the nine cover types. Those nine hundred points were compared with the identification label obtained for each of them in the eight classifications.
Confidence intervals may be more useful than significance test in multiple comparisons. Confidence intervals show the degree of uncertainty in each comparison in an easily interpretable way. Considering this, a BOnferroni confidence interval test was adopted to evaluate the classification performance of each of the eight approaches for the nine cover types.
The results of the BOnferroni test are presented in Table 7. The eight approaches of classification were evaluated for each cover type.
There was not an approach that could be considered different from the others for all the nine cover types.

Approaches I and II were considered non significantly different for the nine cover types. Approaches I and V were not considered different for cover types industry, soils and water. Approaches II and III were considered different for the cover type roads, and approaches VI and VIII where considered significantly different for the non-vegetated cover types.

Table 7. Percent correct classification of nine major cover types by each classification approach.

Classification Approach	COVER				TYPES					Overall Performance
	Corn	Forest	Grass	Industry	Roads	Soils	Soybean	Urban	Water	
I	100 a *	100 a	79 a	90 a	84 a	93 a	100 a	97 a	100 a	93.7 %
II	95 a	89 ab	65 ab	83 ab	76 ab	88 ab	99 a	89 ab	100 a	87.1 %
III	99 a	98 a	75 a	87 a	81 ab	80 ab	99 a	98 a	100 a	90.8 %
IV	92 a	73 c	63 ab	83 ab	71 ab	73 b	98 a	92 ab	100 a	82.8 %
V	53 bc	78 bc	22 d	85 a	62 b	80 ab	86 b	64 cd	100 a	70.0 %
VI	49 bc	88 abc	50 bc	75 ab	74 ab	74 b	86 b	60 d	100 a	72.9 %
VII	64 b	55 d	40 cd	66 b	82 a	73 b	86 b	58 d	100 a	67.4 %
VIII	44 c	77 bc	67 ab	36 c	38 c	49 c	85 b	78 bc	100 a	63.8 %
MSE (%)	14	13	21	15	14	17	6	14	---	

* Within each cover type, approaches followed by the same letter are not significantly different at = 0.05 level by the Bonferroni T - test. (Degrees of freedom = 792, Critical value of T = 3.13)

4.12 Computer time evaluation

Considering classifiaction approach I as the standard procedure, the CPU time consumed for the Maximum Likelihood Classifier in this approach (7,783 secs) was considered as the reference time to compare with the other approaches.
A reduction in CPU time is result of less channels used in the classifications.

Table 8. Computer time (CPU) consumption for each approach.

Classification Approach	CPU Time Ratio
I	1 : 1
II	1 : 1.3
III	1 : 1.3
IV	1 : 1.3
V	1 : 2.5
VI	1 : 2.6
VII	1 : 4.0
VIII	1 : 4.5

5 CONCLUSIONS

The four data sets examined in this research provide a method for evaluatting the effect of the TM thermal infrared band in multispectral classifications. A Per Point GAussian Maximum LIkelihood classification was performed with eight different approaches. The analysis of the data sets with all seven bands or the six reflective bands (i.e., data sets A and B), provided 37 spectrally separable classes. THe use of four or three Principal Components provide fewer spectrally separable classes.
The use of the seven TM bands for the analysis procedure gave better discrimination among classes and fewer mixed classes. This same situation prevails between data sets C and D where the use of three Principal COmponents gave more mixed classes than set C.
The use of the seven TM bands gave the best minimum and average separability values. If the thermal band is not included for multispectral classification, then it is better to generate the training statistics (cluster) without the thermal band.
Water features show to be equally discriminated with all the approaches. Soybean and corn were better discriminated with classifications of the data set A. Urban classifications using statistics generated with the seven TM bands (data set A) were significantly different from those of the other three data sets.
Soils and industrial classes in the approach VIII (Three Principal Components) were significantly different and had the lowest accuracy mean values. Classifications performed with data sets B, C and D provided fores/corn mixed classes because of lower separability values between those features.
In general, classifiactions using the thermal band were significantly different from classifications without this band. THe separability values between pairs of classes were higher when the thermal band was used.
When there is a constraint on computer time and/or hardware, the use of data compression techniques such as PRincipal Components may be advantageous due to the drastic decrease in CPU time consumed.
The thermal band itself has great possibilities for specific types of research, specially in the areas of thermal pollution mapping, detection of vegetation in stress situations and mapping of sea currents.

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