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A Hybrid Methodology For Detecting Cartographically Significant Features Using Landsat TM Imagery

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A general Change Detection (CD) methodology is investigated that involves a hybrid mix of image processing, spectral transformation, and statistical pattern recognition techniques. The Hybrid Methodology attempts to combine various forms of supporting and conflicting evidence for change into a resulting change map. The approach involves differencing registered multiband scene pairs that have undergone a spectral transformation, generating threshold masks, and applying a classifier to the masked multiband scene pairs.

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PREFACE

This effort was conducted in support of a Defense Mapping Agency (DMA) project entitled "Multispectral Image Exploitation Effort."

The effort was performed during the period May to August 1989 under the supervision of Mr. Donald J. Skala, Chief, Exploratory Technology Branch; Mr. James E. Stilwell, Chief, Space Technology Division; and Dr. Joseph J. Del Vecchio, Director, Space Programs Laboratory.

Special acknowledgements are made to James Hammack (DMA), Donald Davis (ETL-SL), and Bob Satterwhite (ETL-RI) for some helpful insights gained through technical discussions, and again to Mr. Davis in creating some of the Ground Truth Maps. Thanks are also extended to James Miller for programming assistance.

Col. David F. Maune, EN, was Commander and Director, and Mr. Walter E. Boge was Technical Director of the U.S. Army Engineer Topographic Laboratories during the study, and during the report preparation.

A HYBRID METHODOLOGY FOR DETECTING CARTOGRAPHICALLY SIGNIFICANT FEATURES USING LANDSAT TM IMAGERY

1.0 INTRODUCTION

1.1 Purpose

The objective of this effort was to recommend a reliable method for detecting and identifying cartographically significant changes using Landsat Thematic Mapper (TM) imagery. In addition to being reliable, such a method should be as automatic and easy as possible for a user to operate. The method must not only be able to detect changes of interest but it must also ignore changes not of interest. Significant changes were defined as new manmade features such as roads, bridges, and buildings; whereas, insignificant changes were shifts in vegetation features.

1.2 Scope

A general Change Detection (CD) methodology was formulated as the result of direct experience gained through numerous CD experiments, as well as a review of past efforts in the remote sensing community. This methodology, which is is a hybrid mix of image processing and pattern recognition techniques, attempts to combine various forms of supporting and conflicting evidence for change into a resulting change map.

The methodology involves differencing registered multiband scene pairs that have (optionally) undergone a spectral transformation, generating a mask by applying a histogram-based threshold to the differenced image, and applying a classifier to the masked multiband scene pairs. The result of differencing the registered scene pairs is used as evidence for change. Following this, the result of subsequently differencing classification maps is used as evidence for NO_CHANGE and effectively acts as a filter to the image-differencing results.

A few specific implementations of the methodology were investigated through a laboratory experiment conducted using the Land Analysis System (LAS) Software residing on the US. Army Engineer Topographic Laboratories (ETL) Space Research Test Bed Facility (SRTF) at Fort Belvoir, Virginia. Ultimately, an operational version of the methodology must take the form of a streamlined software package easily invoked with minimal input by an analyst. Although the details of the experiment as presented may seem to contradict this goal, the author feels they are essential to document the specific nature of the algorithms involved. One advantage of using LAS is that once a sequence of operations is found to be useful for CD, it can be automated to a large degree by using the system's Procedure Definition Files (PDF's) capability.

The most suitable CD methods, along with suggestions for further study, are discussed in the concluding portions of this report. The appendices are used to extend some of the technical ideas as well as to document the actual experimental results. Although the effort was directed at Landsat TM, the proposed methodology could be applied to other multispectral image (MSI) data, such as SPOT Multispectral and Aircraft Multispectral Sensors. The methodology could also be extended to other feature categories.

2.0 CHANGE DETECTION METHODOLOGY

The proposed CD methodology involves a number of processing steps, most of which can be automated. Five major tasks are involved: (1) Extracting registered scenes from source multispectral imagery (MSI); (2) Generating spectrally transformed scenes; (3) Extracting CD feature candidates; (4) Identifying CD feature candidates; and (5) Generating a CD feature map. A diagram of the algorithm flow for these tasks is shown in Figure 1. This section provides a detailed explanation of the processing steps necessary to implement the tasks.

2.1 Extracting a Registered Data Set

This first task is needed to define the regions of interest and to provide a registered data set. At a minimum, image-to-image registration must be performed so that the pixels in the scene of one date correspond to the same ground samples as the pixels in the scene of the second date. For satellite multispectral imagery, such as Landsat TM and SPOT, this process is generally straightforward, so long as the acquisition geometry is near-nadir. In addition to off-nadir satellite imagery, the image-to-image registration of aircraft multispectral imagery is generally quite difficult and involves modeling the sensor's acquisition geometry, its scanning motion, and the platform's motion.

If there is a requirement to overlay the CD results onto a map, one must perform an image-to-map transformation to one of the images. This can be done either before or after the CD processing. However, compute time will usually be quicker if an image-to-image registration is first performed for the two scenes, followed by generating an image-to-map transformation model. Rather than applying the transformation to the scenes, it is applied later to the CD feature map that was generated in the same image space as the scene pairs.

Generally, registering Landsat TM scenes to other dates of Landsat TM or to maps at a 1:100,000 scale or smaller is not a problem. For scenes with fairly flat topography and sufficient control, accurate registration at a 1:50,000 scale can often be accomplished. Further discussion of registration issues is beyond the scope of this report. A number of investigators have studied the problem (for example, see Welsh for one such study[1]) Also, a recent ETL study demonstrated the feasibility of generating 1:50,000-scale image maps and evaluated the necessary processing steps using government software.[2]

2.2 Generating Spectrally Transformed Scenes

Although the differencing of registered scene pairs can be performed directly on the original multiband data, such differencing involves more than one band. In the case of Landsat TM imagery, there are 6 candidate bands (visible and near-infrared) some of which are highly correlated.

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[1] Welsh, R. Jordan, T.R. and Ehlers M. "Comparative Evaluations of the Geodetic Accuracy and Cartographic Potential of Landsat-4 and Landsat-5 Thematic Mapper Image Data", *Photogrammetric Engineering and Remote Sensing*, Vol. 51, No.9 , Sept 1985: pp. 1249-1262.

[2] Rand, Robert. Davis, Donald. and Anderson John. *Multispectral Image Maps from Landsat Thematic Mapper Data.* Fort Belvoir, VA: U.S. Army Engineer Topographic Laboratories, in publication.

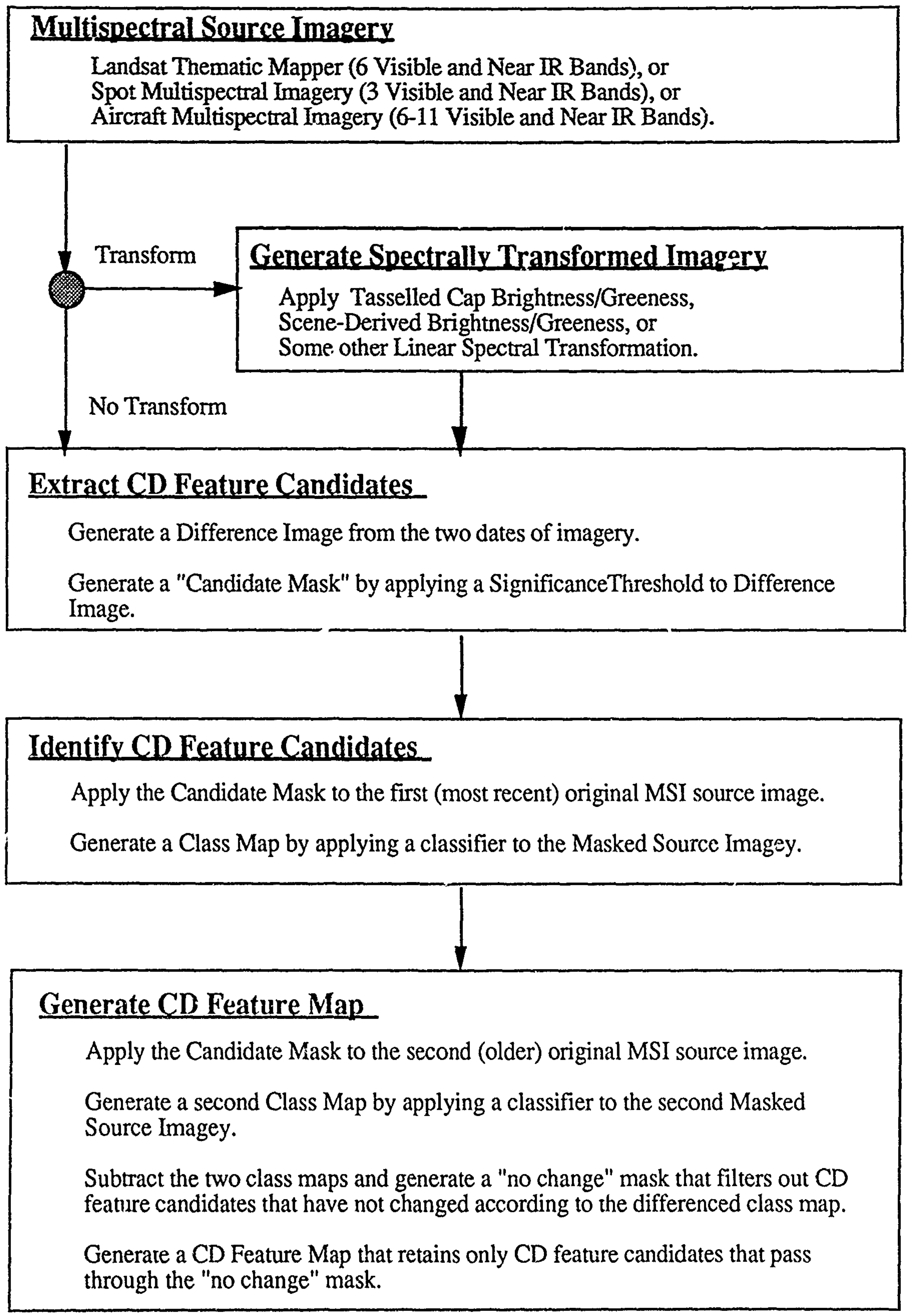

Figure 1. Hybrid Change Detection Methodology Diagram

The presence of multiple bands raises the question of whether to choose a suitable subset or the entire set, where, of course, the suitable subset is very dependent on the target features of interest. The presence of correlated bands raises the question of whether a spectral transformation could be applied to this imagery to improve the performance of a CD algorithm with regards to either accuracy of the final results or execution time of the algorithm. If a spectral transformation is performed, the question is again raised of whether to choose a suitable subset or the entire set of transformed bands.

2.2.1 Properties of Spectral Transformations

There are various types of transformations that can be applied to an image. The term "spectral transformation" is used to differentiate between other types of transformations, such as a geometric transformations used for registering imagery, or spatial transformations for smoothing and sharpening images.

A spectral transformation is a mapping of the pixel values from "observation space" to "pattern space" (sometimes called "feature space"). For MSI, observation space consists of image bands that are the sensor responses in specific wavelength regions. Pattern space is a transformation away from these physical measurements to something else. This something else could be a pattern space that is abstract and difficult to visualize in a physical sense, or it could relate to some other physical quantiy -- perhaps the actual physical classes/objects of interest. As discussed below and in Appendix A, these transformations could be either linear or nonlinear, where linear transformations have certain desirable mathematical properties.

The number of bands of MSI determines the dimensionality of the observation space (e.g. typically $N = 6$ for Landsat TM data). Therefore, it is often convenient to group the observations (pixels) of each ground sample as an N-dimensional pixel vector. The common element to all spectral transformations is that a pixel vector x of dimension N is transformed to pixel vector y with dimension M. Usually $M \leq N$, but this is not necessarily so. M is the number of bands in the transformed image.

In one class of transformations, the objective is to reduce the dimensionality of the data set. Generally, these transformations attempt to generate a minimal number of bands with reduced correlation that also optimize some kind of mean square error criteria. One example is the conventional Principal Component Analysis (PCA) that optimizes with respect to the a single covariance matrix of the image. However, one must be careful in applying such a transformation, since there is not always a correspondence between the correlation (variance/covariance) and mean square error for a set of image bands, and the available information in those bands to allow class separability. For reasons that are discussed in Appendix A, PCA was not considered to be a suitable transformation technique for CD. Another reason is that the resulting transform is highly scene-dependent, and image-differencing methods used in CD are likely to lead to unpredictable results.

There have been attempts to find transformations that generate a minimal number of bands that contain maximum class discrimination ability. Some of these focus on optimizing criteria based on a set of class covariance matrices. Examples are the Canonical Transformation (CT)[3] and Common Principal Component Analysis (CPCA) for k-Groups.[4] These methods are also discussed briefly in Appendix A.

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3 Sing-Tze Bow. *Pattern Recognition - Applications to Large Data-Set Problems.* New York, NY: Marcel Dekker, Inc., 1984.

4 Bernhard N Flurry. "Common Principal Components in k-Groups." *Journal of the American Statistical Association*, Vol. 79, Dec 1984: pp. 892-898.

The CT, CPCA and a number of variations on these techniques are all linear mappings. Unfortunately, a linear transformation that maximizes class separability may not exist. Nonlinear mapping techniques have been proposed by the research community but they are not well studied.[5]

A second class of transformations attempt to generate a suitable number of bands, each of which emphasizes some physical feature or characteristic such as vegetation, soil, urbanness, or wetness. These bands would not necessarily optimize class discrimination. Instead, each band would be optimized to portray some feature of interest. For example, in a wetness band, the bright pixels would correspond to wet features, such as water or wet ground. The dark pixels would correspond to something else; ideally, to dry features. Such transformations can be referred to as characteristic vector transformations.

The transformations investigated in this effort were the Tasseled Cap Brightness/Greenness Transformation and a Scene-Derived Brightness/Greenness using Gram Schmidt Orthogonalization. These transforms can be considered linear characteristic vector transformations.

2.2.2 Brightness/Greenness Transformations

A brightness/greenness transformation is one that reduces the 6-band TM source imagery to 2 bands (components) corresponding to the two physical attributes: brightness and greenness. Brightness is a measure of the overall brightness of a feature across all 6 original bands. Greenness is a measure of the spectral contrast between the visible and infrared bands. The pair of components provides a good discrimination between vegetation and soil features.

As mentioned above, the transformation is applied to both multiband scenes. This produces two spectrally transformed multiband images, each comprised of two bands. An increase in greenness between two dates is evidence of an increase in vegetation content for the ground point in question. If this increase in greenness was accompanied by a corresponding decrease in brightness, supporting evidence is added and the confidence would be higher that this point increased in vegetation content. Conversely, an increase in brightness between two dates is evidence in favor of an increase in soil content, and a corresponding decrease in greenness would add to this evidence. Two methods for producing brightness/greenness were tested -- the standard TM Tasseled Cap and a Scene-Derived Brightness/Greenness transformation.

2.2.2a Tasseled Cap Brightness/Greenness Transformation

The most well-known method for generating brightness/greenness components is the automated TM Tasseled Cap procedure.[6] This method has the advantage that it is entirely automated and scene independent. One set of transformation coefficients is applied to any TM image -- regardless of scene content or season. The potential disadvantage is that the use of such a universal set of coefficients may not always be valid for different scenes and environments.

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[5] Therrien, Charles W. *Decision Estimation and Classification* (Section 5.7 Non-Linear Mapping). New York, NY: John Wiley & Sons, 1989.

[6] Crist, E.P. and Cicone, R.C.; "A Physically-Based Transformaton of Thematic Mapper Data - The TM Tasseled Cap." *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-22, May 1984: pp. 256-263.

The TM Tasseled Cap is a physically based linear transformation of Landsat TM data that captures approximately 95 percent of the total variability of a scene in two components -- brightness and greenness -- having the properties as discussed above. This transformation can also generate a third component, called wetness, that is sensitive to soil and plant moisture; however, this component was not investigated because its physical properties did not seem applicable for the change detection of interest. The technique is basically an extension to an original Tasseled Cap technique developed by R.J. Kauth and G.S Thomas for Landsat MSS data.[7] The Tasseled Cap brightness/greenness coefficients are listed and plotted, along with those of the Scene-Derived Method in Appendix A.

2.2.2b Scene-Derived Brightness/Greenness

Another method for generating brightness/greenness components is an interactive image-derived Gram-Schmidt Orthogonalization Procedure.[8] This procedure has the advantage of eliminating the possible invalidity of using a universal set of coefficients because the transformation is generated via data within the scene.

This procedure requires an analyst to generate interactively statistical training-set data, similar to what is done with conventional supervised classification algorithms. The training set represents end-member classes for wet soil, dry soil, and vegetation. If wet and dry soil features are not present in the scene, other similar feature types may be substituted, as was done during this effort. Although, this training procedure is not difficult, it does involve time and a limited amount of skill. In order that the two dates receive equivalent transformations, it is important that the same ground features be used for both scenes. Therefore, the training features cannot change across dates, and the analyst needs to determine interactively this fact.

The primary disadvantage of this procedure is the reduction in automation. However, the additional training procedure is not actually much of a handicap because later on, during the CD Feature Identification and Screening Processes, it will ultimately become necessary to apply a classifier to both dates. Any of the supervised classifiers require training-set data, and even the clustering methods could use help from training data to establish good seed points. Thus, the training-set collection process could be consolidated into one step and applied to both the spectral transformation and the classifier's training set. As mentioned above, the transformation coefficients are listed and plotted in Appendix A.

2.2.3 Alternative Spectral Transformations

The use of characteristic vector transformations defined by linear discriminant functions may also be suitable for this task. These functions define linear decision surfaces that can generate linearly transformed coordinate axes, which in turn produce transformed images. Some methods that can generate such linear discriminant surfaces are linear classifiers using the Minimum Euclidean Distance Rule, error-correction methods using the Absolute or Fractional Correctional Rules, gradient decent techniques using the Perceptron Criterion or the Relaxation Criterion Functions, minimum-squared error procedures using the Ho-Kashyap or the Widrow-Hoff Methods, as well as Fisher's Linear Discriminant.[9] These transformations were not investigated in this effort; however, they are good candidates for

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[7] R.J. Kauth and G.S. Thomas. "The tassel cap -- A graphic description of the spectral-temporal development of agricultural crops as seen by Landsat". *Proceedings for the Symposium on Machine Processing of Remotely Sensed Data*, Purdue University, West Lafayette, Indiana: 1976.

[8] Ray Jackson. "Spectral Indices in N-Space." *Remote Sensing of Environment*, Vol. 13, 1983: pp. 409-422.

[9] Sing-Tze Bow. *Pattern Recognition - Applications to Large Data-Set Problems*. New York, NY: Marcel Dekker, Inc., 1984.

a follow-up study that compares the performance of various spectral transformations for use in CD.

One thing in common with all the characteristic vector techniques is that they develop a transformation that attempts to portray certain physical features. The Tasseled Cap portrays soil and vegetation. Other transformations could portray a user-defined set of features (e.g. water, asphalt, concrete, metal, etc.).

Other alternative candidates for CD were mentioned briefly in Section 2.2.1. In particular, the effect of CPCA on MSI data has never been studied. The CT has been studied, but not in this context.

2.3 Extracting CD Feature Candidates

An image-differencing and thresholding technique is applied to the individual bands and a mask is generated using a logical "OR" operation. This mask is called a CD Feature Candidate Mask and is used to extract CD feature candidates from the multispectral source imagery. Mask values of zero designate NO_CHANGE and values of non-zero indicate CHANGE. Subsequent tasks will identify and filter these feature candidates. The mask could also be used itself as an automated stand-alone CD product. A similar image-differencing and threshold method, applied to untransformed multispectral scene pairs, was explored in a prior ETL study.[10]

As its name implies, image differencing is the process of subtracting two images. For example, call the images of the scene pair (generated by a brightness/greenness transformation) BG_DATE1 and BG_DATE2 with components as follows:

Date 1:	BG_DATE1(BRIGHT) BG_DATE1(GREEN)
Date 2	BG_DATE2(BRIGHT) BG_DATE2(GREEN)

The image-differencing process results in one differenced image that can be called BG_DIFF with components that are calculated as

BG_DIFF(BRIGHT) = BG_DATE2(BRIGHT) - BG_DATE1(BRIGHT)
BG_DIFF(GREEN) = BG_DATE2(GREEN) - BG_DATE1(GREEN)

Note immediately that the values for this differenced image can be both positive and negative. If the original images (BG_DATE1 and BG_DATE2) have the typical 8-bit integer range of 0 to 255, then the differenced image (BG_DIFF) will have a range of -255 to 255. The largest and smallest (largest negative) values correspond to points that have most likely changed.

[10] James Wickham. *Land Cover Change Mapping Using Landsat Thematic Mapper Data.* performed by Earth Satellite Corporation for U.S. Army Engineer Topographic Laboratories (Attn: CEETL-SL T (Rand)), Fort Belvoir, VA. July 1988.

If the two original images were calibrated with respect to each other (by removing the effects of environmental factors such as atmosphere and solar illumination), then the points least likely to have changed would have a value near zero in the differenced image. If such a calibration is not performed, the effect should manifest itself by a shift in the differenced image's histogram. Instead of a histogram peak (corresponding to NO_CHANGE) hovering about the value of zero, it is likely to hover about some other positive or negative value that reflects a lack of calibration. However, such a shift (if not too large) should not affect the ability to detect significant changes.

A mask is generated, using a two-tail statistical inference method, that identifies CD feature candidates. A null hypothesis is formulated that the predominant distribution in a differenced band's histogram corresponds to NO_CHANGE. The alternate hypothesis is CHANGE. Therefore, if there is sufficient evidence to reject the null hypothesis of NO_CHANGE, then the alternate hypothesis of CHANGE is accepted. This evidence comes in the form of a threshold, commonly known as significance value Alpha (α), that corresponds to data in the tails of the distribution.

The decision-making rationale is as follows: A value of $\alpha = .05$ corresponds to 2.5 percent of the data residing in each of the two tails of the distribution and is basically interpreted to mean there is a 5 percent chance of making a "Type I Error" in rejecting the null hypothesis of NO_CHANGE. This would also correspond to a 5 percent "false alarm" rate in detecting changes. Reducing this false alarm rate can be accomplished by reducing alpha; however, it will come at the expense of increasing the chance of making a Type II Error Beta (β) -- accepting NO_CHANGE when it should have been rejected. Reducing α further is likely to cause the CD processor to miss a greater number of changed features. Therefore, one advantage of the hybrid methodology is that it can allow the Type I (false alarms for change) error to remain somewhat high during the first step so that any potential change candidates are not missed, which is perhaps a good idea during the image-differencing step, particularly if the subsequent thresholds are to be selected based on an assumption that the differenced image's histogram is predominantly a normal distribution representing NO_CHANGE.

The threshold range (in pixel values) is defined by selecting an alpha value and determining the pixel range for which the probability $p \leq \alpha$. One parametric method of defining the threshold is to assume that the predominant distribution is normal (Gaussian) and represents NO_CHANGE. Using this assumption (not necessarily valid), $\alpha = .05$ yields a threshold range of $\{x_1 \cup x_2: x_1 \leq (\mu - 2\sigma); x_2 \geq (\mu + 2\sigma)\}$. An alternate nonparametric method of defining the threshold range could be used by first selecting an alpha value, and then empirically determining the pixel range directly from the histogram distribution without making assumptions of normality. If $\alpha = .05$ is selected, then the range would be defined by an x_1 that contains 2.5 percent of the smallest pixel values and an x_2 that contains 2.5 percent of the largest pixel values.

A mask is generated for each band by remapping all pixels that do not reside within the range $\{x_1 \cup x_2\}$ to a background mask value (MV) of MV=2. Since the pixels in the range x_1 obviously correspond to a different type of change from the pixels in the range x_2, the mask can represent this change by different mask values -- the x_1 pixels could be set to a mask value of MV=1, and the x_2 pixels could be set to a value of MV=3.

Continuing with the above example using brightness/greenness measures, the values of MV = 1, 2, 3 can be interpreted as follows:

Masking of BG_DIFF(BRIGHT)	MV = 1	DECREASE IN BRIGHTNESS
	MV = 2	NO CHANGE
	MV = 3	INCREASE IN BRIGHTNESS
Masking of BG_DIFF(GREENNESS)	MV = 1	DECREASE IN GREENNESS
	MV = 2	NO CHANGE
	MV = 3	INCREASE IN GREENNESS

Combining the masks with a Logical "AND" operation can produce the nine mask value combinations listed in Table 1:

Table 1. Brightness/Greenness Mask Combinations.

MVs =	(2,2)	NO CHANGE IN BRIGHTNESS	AND	NO CHANGE IN GREENNESS
MVs =	(2,1)	NO CHANGE IN BR 'ITNESS	AND	DECREASE IN GREENNESS
MVs =	(2,3)	NO CHANGE IN BRIGHTNESS	AND	INCREASE IN GREENNESS
MVs =	(1,2)	DECREASE IN BRIGHTNESS	AND	NO CHANGE IN GREENNESS
MVs =	(1,1)	DECREASE IN BRIGHTNESS	AND	DECREASE IN GREENNESS
MVs =	(1,3)	DECREASE IN BRIGHTNESS	AND	INCREASE IN GREENNESS
MVs =	(3,2)	INCREASE IN BRIGHTNESS	AND	NO CHANGE IN GREENNESS
MVs =	(3,1)	INCREASE IN BRIGHTNESS	AND	DECREASE IN GREENNESS
MVs =	(3,3)	INCREASE IN BRIGHTNESS	AND	INCREASE IN GREENNESS

Combining the above masks with a logical "OR" operation can produce other masks. For example, the operation { $MV(3,2) \cup MV(3,1)$ } flags pixels that are very likely to be a change from vegetation to construction (soil) or urban (concrete). Such a mask retains pixels that have either an "INCREASE IN BRIGHTNESS AND NO CHANGE IN GREENNESS" or an "INCREASE IN BRIGHTNESS AND DECREASE IN GREENNESS".

2.4 Identifying CD Feature Candidates

The CD feature candidates are identified by masking the most recent scene (original MSI source image) with the CD Feature Candidate Mask and then applying a clustering operation, or classifier, to the masked scene. Although there are a numerous clustering operations and classifiers that could be used, this study will restrict itself to three methods available under LAS -- an unsupervised **ISOCLASS** clustering algorithm, a supervised **Minimum Euclidean Distance** classifier, and a supervised **Bayesian** classifier. The results of identifying the CD feature candidates is a "**CD Feature Candidate Map**".

2.4.1 Clustering Method Tested

The ISOCLASS algorithm available under LAS is a slight modificaton of the well-known ISODATA (Iterative Self-Organizing Data Analysis Techniques A) algorithm developed by Ball and Hall.[11] ISODATA belongs to the category of clustering algorithms that seek to minimize a specified objective function. Another category of clustering algorithms is based on graph-theoretic methods. A third category is based on heuristic methods.

In the case of ISODATA, the objective function is a double summation of the distances between samples and cluster centers. The first summation is the sum of distances between

[11] G.H. Ball, and D.J. Hall. *Isodata, A Novel Method of Data Analysis and Pattern Classification.* Stanford Research Institute Technical Report, (NTIS AD699616) Stanford, CA. 1965.

each sample and its corresponding cluster center. The second summation is a sum over all the clusters. Depending on the actual implemention, the measure of distance could be either Euclidean or City-Block. ISOCLASS uses the City-Block distance.

ISODATA/ISOCLASS is an iterative procedure, whereby clusters are continually split and merged. Acheiving a local minimization of the objective function is easy, as it occurs when each of the samples in a data set has been assigned to the nearest cluster center. Such a solution is found at each iteration of the algorithm. However, as will be discussed, a unique global solution for the data set cannot be guaranteed.

A brief sketch of the ISODATA/ISOCLASS procedure is as follows:

> Acting on an initial estimate for the mean vectors (center points) of seed clusters, ISODATA assigns samples in the data set to the nearest seed cluster. The mean vectors for each cluster are then recomputed based on the sample assignments. The standard deviation for each band is also computed.
>
> A split /merge sequence of iterations then acts to create new clusters and merge others. During a split iteration, a cluster is split into two clusters if the band containing the largest standard deviation is greater than a specified threshold STDMAX. The split is made along the coordinate axis represented by this band. During a merge iteration, two clusters are merged together if the distance between them is less than a specified threshold DLMIN. The sequence is one distinguishing characteristic between ISODATA and ISOCLASS. Generally, the sequence for ISODATA is SCSCSCSC... (split on odd iterations, combine on even iterations). ISOCLASS begins by splitting clusters, and continues to split them until eighty (80) percent of them have standard deviations less than the specified STDMAX, after which an altenating sequence begins. For example, the sequence would look something like SSSSSSCSCSC...

ISOCLASS also has a chaining mechanism that was added to the ISODATA process. Chaining allows clusters to be joined together in chains after the split/merge sequence, in an attempt to model non-Gaussian shaped distributions. Theoretically, rather bizarre shapes could be modeled (e.g. donunt-shaped or S-shaped clusters often seen in Astronomical objects such as in Ring Nebulaes and S-shaped Galaxies). However, because we are concerned with spectral rather than spatial classificatioin, Gaussian clusters are probably appropriate models, so that chaining is not necessary.

An analyst using ISOCLASS can use its default parameters for minimal interaction, or a priori knowledge about the data set for potentially better performance. The default set of initial seed clusters is a single cluster with its mean vector and standard deviation computed from the entire data set. Better performance could potenially be acheived by specifying to the algorithm a statistics file containing sample statistics of known ground features obtained from the data set. However, usually the motivation for invoking a clustering method is that either very little a priori knowledge about the scene is available, or that there is insufficient time to perform an alternative supervised learning method. Therfore, this CD effort only studied the effect of using the default seed cluster.

As mentioned above, one problem in using ISOCLASS is that finding a unique global solution can be difficult. This clustering technique may settle into a local rather than global solution (i.e. the minimized value of the objective function is not a global minimum). The local solution generally depends on the initial starting estimates for the seed clusters. Specifying different seed points for the initial clusters will probably produce different classification outputs. The differences may not be significant. Nevertheless, a unique solution can never be guaranteed.

Another problem is convergence. ISOCLASS has a tendancy not to converge to a fixed number of clusters and must be terminated with a parameter specifying the maximum number of iterations.

When the clustering process is completed, an analyst must make a physical correspondence between the solution clusters and the corresponding ground features. For broad categories of features, such as deciduous and coniferous trees, water, asphault, and concrete, this task is probably not difficult using a conventional false-color band combination of multispectral imagery. Identifying finer categories are likely to be a problem. This could pose some difficulty during the subsequent post-classification screeening process of the CD feature data, since it is necessary to match clusters between dates. The problem will be discussed further in the Section 2.5; however, suffice it to say that if automation is a key issue, the results generated up to this point are likely to produce valuable information without going through the screening process, and could be useful by themselves as CD products.

2.4.2 Supervised Classifiers Tested

Two supervised classifiers were tested for identifying CD features: the Minimum Euclidean Distance classifier and the Bayesian classifier. The primary advantage to supervised classification methods is that they will produce a consistent set of feature classes later on during the screening process when it becomes necessary to classify the second scene.

Of the two classifiers, the Minimum Euclidean Distance classifier is the simplest and fastest. It is also a linear classifier, meaning that the decision surfaces are lines/planes. Unless the dimensionality of the image data is quite high, it is also likely that such linear surfaces will be inadequate to segment the imagery into the required classes.

The Bayesian classifier is more complex and computationally slower. However, from a statistical point of view, it is also optimal because it minimizes the probability of classification error. This classifier is quadratic and generates decision surfaces that are curves/hyperplanes. Since this is also a parametric classifier, most implementations (such as in LAS) assume the class data belong to multivariate distributions (MVN). The MVN assumption allows the distributional properties of each class to be completely specified by a mean vector and covariance matrix (see also Appendix A).

The major source of Bayes classification error usually comes from inadequately modeling the class distributions, or in overlapping distributions. Sometimes this error is attributed to falsely assuming that these distributions are MVN; however, it is highly likely that the real problem is mixed pixels comprised of more than one feature. Mixed pixels in a training class will cause the class variance estimate to be too high and give the class distribution too high a spread. Ideal training classes should have low variance/covariance to reduce the overlap between classes. Mixed pixels in remaining image data can skew the pixel vector intensities toward the wrong class, resulting in misclassifications.

Both of these methods require training the classifier on a set of classes. For this study, the following classes should be represented: water, concrete, metal, asphalt, deciduous trees, and coniferous trees. With minimum training, these classes are not usually difficult for an analyst to recognize. The primary problem is likely to be mixed pixels. In urban areas, it is difficult to find pure pixels (at 30-meter resolution) of concrete, asphalt, or metal. Typically, pixels will be a mixture of these materials.

Note that the classes used for training a classifier are also the same kind used in generating the scene-derived spectral transformations discussed earlier (e.g. transformations produced by Gram-Schmidt Orthogonalization, Linear Discriminant Functions). Therefore, one interactive session should suffice for training both the classifier and the spectral transformation. An important factor, however, is that the same ground features be used for both scenes. Therefore, the training features cannot change across dates, and the analyst needs to determine interactively this fact.

2.4.3 Alternative Clustering Methods

The problems of uniqueness and convergence mentioned in Section 2.4.1 are typical of most clustering methods, and considerable effort has been made to overcome them by modifying the approach. One approach by Ismail and Kamel is a hybrid search strategy that alternates between a breadth-first search and a depth-first search for an improvement (decrease) in the objective function.[12] Samples are moved from one cluster to another and all possibilities are examined. In breadth-first search a pattern is moved if the reassignment results in the best improvement to the objective function. In depth-first search a pattern is moved the first time it results in an improvement to the objective function.

Another approach is the Mixture Model clustering method. A data set is assumed to consist of a mixture of several multivariate normal (MVN) populations, each corresponding to a ground feature. The maximum likelihood approach is used to compute maximum likelihood estimates (MLE's) of the mixing proportions π_k, mean vectors μ_k, and covariance matrices Σ_k corresponding to each underlying population. Various model selection criteria have been proposed including hypothesis testing (e.g. likelihood ratios)[13] and information-theoretic testing (e.g. Akaike's Information Criterion, and Schwarz' Criterion).[14] A notable difference between the Mixture approach and ISODATA is the use of the covariance structure of the data: ISODATA only considers the variance. Also, because of the use of MVN models, belonging probabilities can be assigned to each pixel.

An entirely different approach to clustering that generates solutions independent of initial seed points belong to the categ -y of graph-theoretic methods. Initial attempts at clustering using this approach were based on constructing minimal and maximal spanning trees (MSTs);[15] however, these methods were also easily corrupted by statistical outliers. A method that seems to be promising is based on constructing either a Relative Neighborhood Graph or a Gabriel Graph.[16] Clusters are then formed by breaking this graph according to edge inconsistencies.

These alternative clustering methods offer potential improvements if substituted into the proposed CD methodology. However, software to test these algorithms has not yet been implemented on ETL's SRTF.

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[12] M.A. Ismail, and M.S. Kamel. "Multidimensional Data Clustering Utilizing Hybrid Search Strategies." *Pattern Recognition*, Vol. 22, No.1,1989: pp. 75-89.

[13] R.K. Lennington , C.T. Sorensen , and R.P. Heydorn. "A Mixture Model Approach for Estimating Crop Areas from Landsat Data." *Remote Sensing of Environment*, Vol. 14, January 1984: pp. 197-206.

[14] Hamparsum Bozdogan. *Determining the Number of Component Clusters in the Standard Multivariate Normal Mixture Model Using Model-Selection Criteria.* Technical Report No. UIC/DQM/A83-1. Army Research Office, June 1983.

[15] Sing-Tze Bow. *Pattern Recognition - Applications to Large Data-Set Problems.* New York, NY: Marcel Dekker, Inc., 1984.

[16] Roderick Urquhart. "Graph Theoretical Clustering Based on Limited Neighborhood Sets." *Pattern Recognition*, Vol. 15, No. 3, 1982: pp. 173-187.

2.5 Generating a CD Feature Map

In the prior task, a clustering operation or supervised classifier was applied to the most recent scene (original MSI source image) to identify the CD features. However, these identified features are still only CD candidates, and additional evidence could be used to screen out false alarms and increase our confidence in the process. The final CD feature map is generated by incorporating conflicting evidence of NO_CHANGE that is supplied by differencing the class map derived from the most recent scene and the map derived from the earlier scene. This method is referred to as post-classification subtraction.

2.5.1 Post-Classification Subtraction

In a prior ETL study, the Post-Classification Subtraction (PCS) method was investigated as a technique for detecting change.[16] Each of the registered scenes was classified using a Minimum Euclidean Distance classifier and the resulting class maps were subtracted. The method did not produce acceptable results, primarily because of the classifier's error rate. If a classifier had a 0.0 percent error rate for both dates, then the resulting CD map would have no errors. However, this performance will quickly deteriorate even for small classification error rates, because any misclassification on either date will produce a CD map error. The CD errors (mostly false alarms) will quickly propagate and produce unacceptable results. For example, suppose a classifier's overall error rate on each image were 14 percent (a reasonable and perhaps optimistic assumption) and that half the errors overlap. This situation is likely to produce a combined CD error rate of about 21 percent. Therefore, 21 percent of the image pixels could be falsely tagged as change, and this percentage does not include the actual changes. Note that this percentage (21 percent) corresponds to a lot of change!

Rather than use the PCS method as evidence for change, suppose it is used as evidence for NO_CHANGE. That is, let the PCS method be used to identify ground points that don't change, and use these identified points to screen out (eliminate) the feature candidates identified during the image-differencing process. Since there are more ways for a classifier to be wrong than to be right, a classifier's error rate should not affect a decision of NO_CHANGE as much as a decision of CHANGE. Whereas an error rate of 14 percent (above) adversely affected a classifier for detecting CHANGE, it should not be as harmful as a screening mechanism for detecting NO_CHANGE.

As an example, suppose there were five classes defined as the classification set {WATER, ASPHALT, CONCRETE, DECIDUOUS_TREES, and CONIFEROUS_TREES}. *A priori*, there is a 20 percent chance of being correct and an 80 percent chance of being wrong, without input from a classifier. This fact, along with fairly good classification accuracy (say, 86 percent in the previous examples) of a classifier, causes PCS to yield a fairly strong statement when it gives conflicting evidence against the image differencing results that produced the CD feature candidates.

In order to usethe PCS method, apply the same clustering operation or classifier that was applied to the most recent scene for identifying the CD feature candidates to the older scene (masked by the CD Feature Candidate Mask). Obviously, each clustering/classification run must have the same set of classes; the class values must be numeric, with values CV = 1, N (where N is the number of classes); and the class values for each run must correspond to one another. For example, if the classification set for the first date is {WATER,

[16] Wickham, James. *Land Cover Change Mapping Usirg Landsat Thematic Mapper Data.* performed by Earth Satellite Corporation for U.S. Army Engineer Topographic Laboratories (Attn: CEETL-SL-T (Rand)), Fort Belvoir, VA. July 1988.

ASPHALT, CONCRETE, DECIDUOUS_TREES, and CONIFEROUS_TREES}, the classification set for the second date should be the same. If the class value CV=2 represents asphalt on the first date, it must also represent asphalt on the second date. One exception to this rule is for the supervised classification case of a class designated as UNKNOWN. This exception will be discussed later.

As briefly mentioned in Section 2.4.1, unsupervised ISOCLASS clustering can present problems to the PCS method. The clustering/classification runs must produce a matched set of classes with CV's that correspond to one another. There is no guarantee that the clusters produced from the first run of ISOCLASS correspond to the clusters of the second run. For example, if the cluster limit for both runs is set equal to CL=5, ISOCLASS's cluster set for the first run would probably be {CLUST01, CLUST02, CLUST03, CLUST04, CLUST05}, and its cluster set for the second run would also probably be {CLUST01, CLUST02, CLUST03, CLUST04, CLUST05}. The class names are the same and so are the class values. But do they actually correspond to the same features? Since the clustering was performed on a masked pair of images that already represent pixels with the greatest likelihood for change, there is definitely a chance that the features do not correspond.

The ambiguity presented to the PCS method by unsupervised clustering can likely be solved by invoking a statistical distance measure, such as the Divergence Measure or the Bhattacharyya Distance.[17] Either of these measures could be used to match corresponding clusters between dates. The intersection of the two sets of clusters could be used as a PCS filter.

The PCS method is applied by subtracting the class map results from each run. This process results in a PCS filter map containing non-zero (positive and negative) integers that designate CHANGE and a value of zero that designates NO_CHANGE. Note that if an UNKNOWN class is included in the classifier's feature set, then the class value should be set to a different number for each date; otherwise, the PCS process will designate the difference in two unknown classes as NO_CHANGE. Obviously, if the class in each date is unknown, one cannot know that the underlying features did not change.

Although the PCS method should reduce false alarms (Type I Error), it will do so at the risk of eliminating valid CD features (increasing Type II Error). This risk was studied during the laboratory experiments.

2.5.2 Applying the PCS Filter Map

The final CD Feature Map is generated by overlaying the PCS Filter Map onto the CD Feature Candidate Map. During the overlay process, those pixels which have a value of zero in the filter map and any value in the image-difference map are set to some arbitrary constant (say, CV=100) in the final CD Feature Map. For any nonzero value in the filter map, the CD Feature Map retains the value in the candidate map.

This process effectively tags the filtered features with a class value that can be considered a class type "FILTERED". At this point, an analyst could have the option of interactively editing individual "FILTERED" features, or automatically setting them to the background that designates NO_CHANGE.

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[17] Therrien, Charles W. *Decision Estimation and Classification*. New York, NY: John Wiley & Sons,1989.

2.6 Seasonal Issues Affecting CD Results

The simplest CD scenario occurs for scene pairs representing different years, but the same season. In such a case, most of the vegetation features will be approximately at the same point in their growth cycle; therefore, the spectral reflectance of vegetation features will be fairly close in both scenes. Of course, some vegetation features could become stressed or unhealthy in one of the scenes and exhibit a corresponding spectral change. In fact, numerous environmental effects could cause a shift in the spectral properties of many natural features. Nevertheless, the effect is still minimal compared to scenes acquired from different seasons. Optimal CD processing results are thus likely to be achieved when scene pairs are acquired for the same season.

In considering biseasonal change detection, certain seasonal combinations are likely to be more favorable than others. If an analyst is invoking a brightness/greenness transformation, then the before/after combinations of

fall-to-spring,
fall-to-summer,
winter-to-spring (assuming no snow),
winter-to-summer (assuming no snow),

should produce far better results than the before/after combinations of

spring-to-fall,
summer-to-fall,
spring-to-winter (assuming no snow),
summer-to-winter (assuming no snow).

The reason is that, in the first group, the property of greenness increases from the oldest to the newest scene for vegetation features, and this trend is indicative of new vegetation. Such flagged changes can easily be ignored for cartographically oriented change detection. In the second group, however, the property of greenness decreases and this trend is indicative of new urban features. Such flagged features are likely to increase dramatically the false alarm rate of urban changes.

Recall that the PCS filtering method was introduced to reduce the number of false alarms generated by the initial image-differencing process. Whereas the need for invoking the PCS Filter may be minimal for single-season change detection, the real payoff for this method could be biseasonal change detection. During the classification process, seasonal effects may influence the difficulty in classifying certain vegetation features; however, once complete, the class maps record only class values.

3.0 DESCRIPTION OF LABORATORY EXPERIMENT

The laboratory trials conducted under this effort were done using the LAS Software that resides on ETL's Space Research Test Facility (SRTF) at Fort Belvoir, VA. This software was developed by NASA/Goddard Space Flight Center and USGS/EROS Data Center. The ETL version is currently being supported by EROS. The SRTF hardware supporting LAS consists of a VAX 11/785 computer with a Gould IP8500 Image Processor.

In addition to describing the general experimental approach, much of the discussion in this section is focused on documenting the experimental procedures as they were implemented on LAS. Nete that although the procedures may seem to imply that the methodology is quite tedious, most of the steps identified can be automated. LAS has a facility to implement a sequence of repetitive tasks using Procedure Definition Files (PDF's).

During this experiment, 20 trials were conducted. Eighteen of these trials were performed using the standard TC Brightness/Greenness Transformation. Of these 18, 16 tested a single-season scenario and the performance of various classifiers as well as parametrically and nonparametrically derived change masks in an attempt to identify the best performing classifiers and masks. The other two trials of the 18 tested a biseasonal change scenario using the Bayesian classifier and a parametrically derived change mask. The other two of the 20 trials tested the Scene-Derived Brightness/Greenness transformation with the Bayesian classifier (single season, parametric). A listing of these trials can be found at the end of this section in Table 5.

3.1 Source Data and Test Site Selection

Landsat Thematic Mapper (TM) Imagery was used as the source imagery. In order to get a representative data set of cartographic significant features and backgrounds, as well as seasonal variations, a Multiscene/Multitemporal Montage Data Set of Landsat TM data was used. This data set was recently generated by ETL for conducting experiments in terrain analysis and change detection. The study area is a representative sampling over a full scene of Landsat TM (approximately 185 * 185 square km) covering the Washington D.C., Virginia, and Maryland region. Four dates of imagery were acquired: May 1985, August 1985, October 1985, and May 1987. The multidate/multiscene montage concept is illustrated in Figure 2.

Multiple date coverage allows various pairwise scenarios:

May 1985	to	May 1987	(same seasons, different years)
Aug 1985	to	May 1987	(different seasons, different years)
Oct 1985	to	May 1987	(different seasons, different years)

Since adequate ground truth coverage of the full mosaic scenes is still underway, a selected subset was extracted for this effort's experiments. Also, due to time limitations, only two of these combinations were tested -- May/May and Oct/May. The testing of the other seasonal combinations is strongly recommended.

Figure 3 shows a radiometrically enhanced color print of the complete (1024 * 1024) study area for May 1987. The RED-GREEN-BLUE band combination is B4-B7-B2. In Section 4.0, Figures 4 and 5 show the same type print (at a larger scale) extracted from a selected 512 * 512 subset for May 1985 and May 1987, respectively.

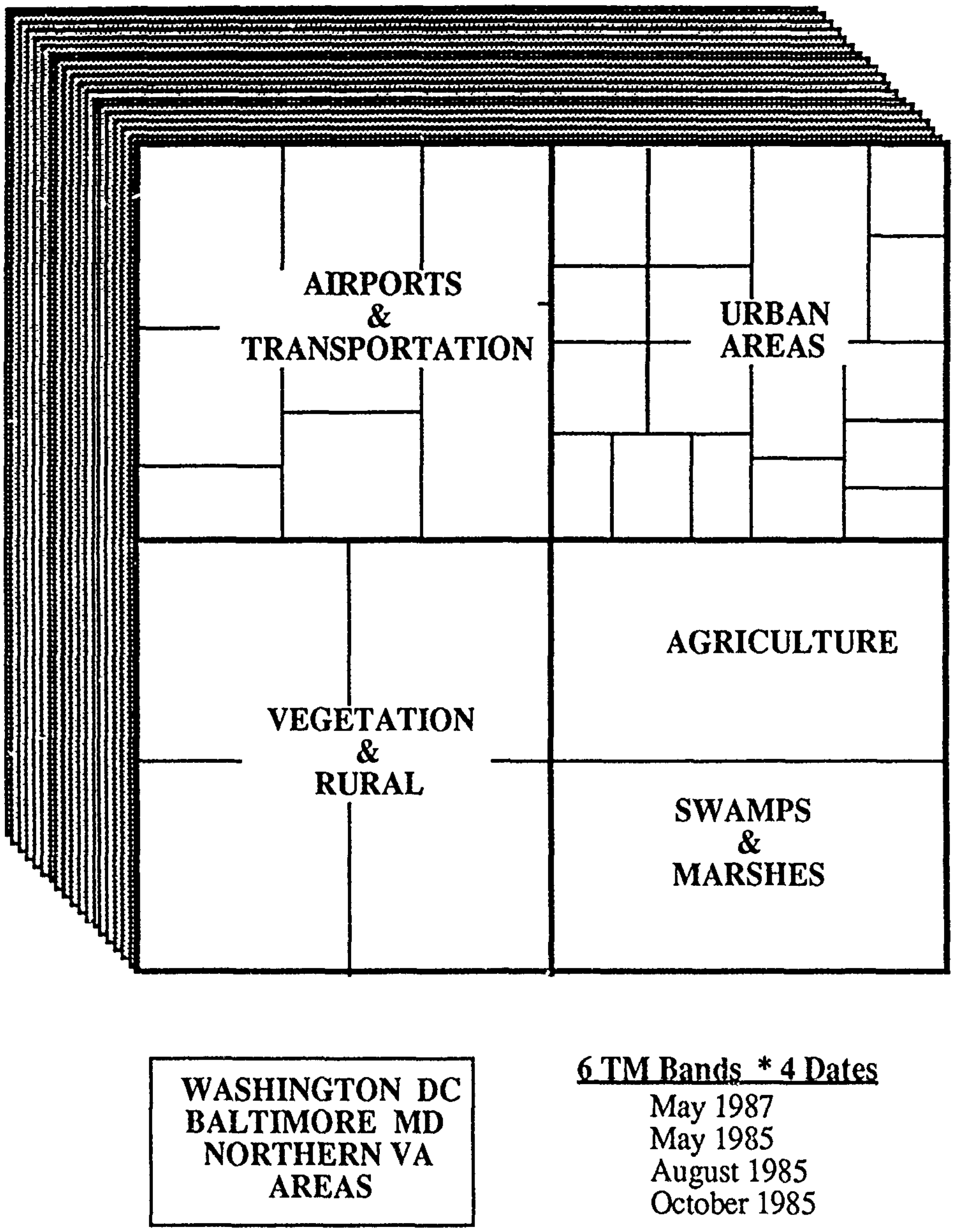


Figure 2. Multidate/Multiscene Montage TM Data Set

Figure 3. Radiometrically-Enhanced May 1987 Scene of Complete Study Area
(B4-B7-B2)

3.2 Standard TC Brightness/Greenness Trials

As mentioned above, 18 of the laboratory trials (see Table 5) were conducted using the standard Tasseled Cap Transformation. Sixteen of these trials tested a single-season CD scenario, using the May/May scene pair with either the CD mask generated by the parametric thresholding method (Trials 1, 2, 3, 4, 5, 6, 7, 8, 17, 18, 19, 20) or the CD mask generated by the nonparametric thresholding method (Trials 9, 10, 11, 12).

Biseasonal effects were evaluated in Trials 13 and 14 using the Oct/May scene pair. Since the processing steps are essentially the same for single-season and biseasonal pairs, only a detailed description for processing the May/May scene pair is given. The major difference between the trials for the two pairs is the greater extent to which the single season pair was investigated. Only the two more suitable of the four classifiers and the most suitable CD mask was selected for testing the biseasonal scene pair. Also, the PCS step was not tested for the biseasonal case, due to time constraints.

3.2.1 Generating the Tasseled Cap Transformation

The first step was to produce brightness and greenness bands for each of the two 6-band Landsat TM scenes. This was done using an LAS program called **FACTOR** that generates a linear transformation based on an input set of transformation coefficients. As mentioned earlier, these coefficients are listed in Appendix A. **FACTOR** produces an image file with a data type of REAL*4, with values that can be both positive and negative.

To view the brightness and greenness images on a display, it is necessary to radiometrically remap the REAL*4 pixel values, based on the image statistics and convert the images to a data type BYTE (8-bit integers). Although it is possible to do this through an automatic conversion with one of the LAS programs, better visual results are obtained if the conversion is done interactively in separate steps. Appendix B discusses two methods of performing this radiometric mapping.

The brightness and greenness scene pairs were viewed during the experiment to gain a better feel for what the Tasseled Cap transformation was doing, as well as to visually verify that the transformation procedure was implemented correctly. However, note that such viewing is not actually part of the proposed Hybrid CD methodology.

3.2.2 Extracting CD Feature Candidates

The image-differencing process was invoked using **ADDPIC**. In order to maintain higher precision, as well as to avoid a possible shifting of the data points that could occur during the data type conversion process, the image differencing was performed on the REAL*4 data. The May 1985 scene was subtracted from the May 1987 scene, after which the resulting REAL*4 difference image was converted to the INTEGER*2 data type.

Two methods of defining a threshold range for significant changes in brightness and greenness were investigated. In each case, INTEGER*2 data was used to maintain precision and to preserve data integrity.

Thresholding Method 1 (**parametric**) utilized the differenced image's mean and standard deviation. The complete significance range was taken to be $\{x_1 \cup x_2 : x_1 \le (\mu - 2\sigma)\ ;\ x_2 \ge (\mu + 2\sigma)\}$. Two masks were produced with the program **MAP** using the mapping parameters listed in Table 2.

Table 2. Parametric Brightness/Greenness Mask Values.

	Physical Property	Threshold	Input Range	Output
Mask 1	DECREASE IN BRIGHTNESS	x_1	-351 to -46	10
Mask 1	NO CHANGE IN BRIGHTNESS	NC	-45 to 23	20
Mask 1	INCREASE IN BRIGHTNESS	x_2	24 to 316	30
Mask 2	DECREASE IN GREENNESS	x_1	-184 to -31	1
Mask 2	NO CHANGE IN GREENNESS	NC	-30 to 31	2
Mask 2	INCREASE IN GREENNESS	x_2	32 to 175	3

In Threshold Method 2 (nonparametric), the range was derived empirically from the histogram, selecting the significance range as a certain percentage of the pixels (approximately 2.5 %) in the tails of the distribution. Two masks for this method were produced with the **MAP** using the mapping parameters listed in Table 3.

Table 3. Nonparametric Brightness/Greenness Mask Values

	Physical Property	Threshold	Input Range	Output
Mask 1	DECREASE IN BRIGHTNESS	x_1	-351 to -44	10
Mask 1	NO CHANGE IN BRIGHTNESS	NC	-43 to 21	20
Mask 1	INCREASE IN BRIGHTNESS	x_2	22 to 316	30
Mask 2	DECREASE IN GREENNESS	x_1	-184 to -35	3
Mask 2	NO CHANGE IN GREENNESS	NC	-34 to 27	2
Mask 2	INCREASE IN GREENNESS	x_2	28 to 175	1

For both methods, Masks 1 and 2 were added using ADDPIC, producing a single mask with 9 values, as shown in Table 4.

Table 4. Combining Brightness/Greenness Mask Values

Logical Operation			MV
NO CHANGE IN BRIGHTNESS	AND	NO CHANGE IN GREENNESS	22
NO CHANGE IN BRIGHTNESS	AND	DECREASE IN GREENNESS	21
NO CHANGE IN BRIGHTNESS	AND	INCREASE IN GREENNESS	23
DECREASE IN BRIGHTNESS	AND	NO CHANGE IN GREENNESS	12
DECREASE IN BRIGHTNESS	AND	DECREASE IN GREENNESS	11
DECREASE IN BRIGHTNESS	AND	INCREASE IN GREENNESS	13
INCREASE IN BRIGHTNESS	AND	NO CHANGE IN GREENNESS	32
INCREASE IN BRIGHTNESS	AND	DECREASE IN GREENNESS	31
INCREASE IN BRIGHTNESS	AND	INCREASE IN GREENNESS	33

Note that certain (combined) mask values are more likely to correspond to cartographically significant changes than others. MV=32 and MV=31 are good candidates for cartographically significant change, whereas, MV=22 indicates NO_CHANGE. The mask values of MV=13 and MV=23 are probably shifts to vegetation and are not generally of interest to cartographic change detection. Other mask values are not quite so obvious, but can perhaps be related to certain changes, after empirically observing the experiment process for a large number of samples.

The CD mask of nine values (for either method) was used in two ways. First, for all but two of the trials, the nine values were reduced to the two values

MV'=0 (NO_CHANGE Candidate)	for MV = {22}
MV'=1 (CHANGE Candidate)	for MV = {11, 12, 13, 21, 23, 31, 32, 33}.

The classification process that followed was then used to identify significant and nonsignificant changes. Second, for Trials 19 and 20, the mask values were reassigned to the two values

MV'=0 (NO_CHANGE Feature)	for MV = {13, 23, 22, 33}
MV'=1 (CHANGE Feature)	for MV = {11, 12, 21, 31, 32}.

The rationale for this second assignment was to relate the nine mask values to actual classes in an attempt to correlate the mask values generated by brightness/greenness image differencing with significant and non significant physical features. If a good correlation could be made, then the need for invoking a classifier to identify CD features (the next step) might not be necessary. For example, if such a correlation could be made for nonsignificant features {MV = 13, 23, 33}, the next step would be to explore color codes that could be assigned to {MV = 12, 11, 21, 32, 31} representing different types of significant changes.

3.2.3 Identifying CD Feature Candidates

Three segmenting methods were tested for their ability to identify CD feature candidates: an unsupervised ISOCLASS clustering operation, a Minimum Euclidean Distance classifier (supervised), and a Bayesian classifier (supervised). As mentioned in the previous section, these clustering/classification methods were applied to the most recent date of the original multiband scenes (not the transformed scenes) -- May 1987.

For processing efficiency, a (two-level) hierarchical classification strategy was used. The mask values obtained from the prior step were used to create a Level_One class map via the program MAP. This was done by remapping the nine mask values into two values representing CHANGE and NO_CHANGE. A program called SPECSTRT was used to stratify the original May 1987 multiband image into two multiband images. The first stratified image contained all the pixels identified as NO_CHANGE in the Level_One Class Map. The second stratified image contained all the pixels identified as CHANGE.

Each of the clustering/classification methods was applied to the second stratified image, producing a Level_Two Class Map containing classified features for Level_One CHANGE class. Since there was no need to process the first stratified image, about 90 percent of the scene's data were eliminated and processing time was reduced considerably.

The program ISOCLASS was used during Trials 7, 8, 9, 19, and 20 for testing the unsupervised ISOCLASS clustering operation. The cluster limit was set to five for Trial 7;

ten for Trial 8; five for Trial 9; five for Trial 19, and ten for Trial 20. For those trials given a cluster limit of ten, the number of clusters was later combined to a smaller number, as indicated in Table 5. Seed points for the clusters remained at the default of zero.

The supervised classifiers required the definition of a training set. For consistency, the same training set was used for both classifiers. Also, training statistics for the supervised classifiers were collected over sites that didn't change between dates. Such sites were selected while flickering the two dates with radiometrically enhanced B4-B7-B2 (RGB) combinations to identify suitable features.

Enhanced images were used for training because the original Landsat TM bands had a rather low dynamic range. Consequently, the human eye is not likely to recognize spectral variability in the unenhanced images that are significant to a classifier. During the training session, an attempt was made to keep the samples as homogeneous as possible.

Six classes were defined as the training set: {BRIGHT URBAN, MIXED URBAN, DECIDUOUS VEGETATION, WATER, PARKING LOT, and CONIFEROUS TREES}. Most of these classes were comprised of more than one site to obtain representative statistical samples. To construct the training set, define polygons by using **PUT-POLY** and convert to a statistics file using **GOF2STAT**. These programs enable the polygons representing different sites to be grouped into classes. At this point, however, only the vertices of the polygons along with the class/site structure, are stored in the statistics file.To collect the mean and covariance statistics for the sites and class, use **STATS-ALL** on the May 1987 scene.

The training site statistics were printed using the LIST option in a program called **EDITSTAT**. In addition to reviewing this printout, **DIVERGE** was run to compute the divergence measure between classes. After a quick analysis of the statistics, the author decided to drop a couple of sites, which was done by using **EDITSTAT** to delete the sites and again using **STAT-ALL** to recompute the statistics.

At this point, two classifiers were tested to identify the CD feature candidates. The program **MINDIST** was used to apply the Minimum Euclidean Distance classifier to the stratified May 1987 image using the statistics file just computed. The program **BAYES** was then used to apply a Bayesian (maximum likelihood) classifier to the same image, using the same statistics file. In each case, the output of the classifier was a class map that assigned each of the pixels in the stratified Level_Two Scene to one of the class members defined by the training set. See Table 5 for a listing of trials utilizing the supervised classifiers.

To make allowance for an unknown class, select options within BAYES to compute an output statistics file and to generate a maximum likelihood probability image. These output files were subsequently used in the program **UNKNOWN**. This program assigned pixels to an unknown class if a pixel's statistics were computed to lie outside the class member distribution, as specified by a significance level. For this experiment a significance value of $\alpha = .05$ was selected.

Most of the trials tested the parametrically defined mask (Table 2). A few others tested the nonparametrically defined mask (Table 3).

Finally, each Level_Two Stratified Class Map was consolidated back into a Level_One Class using the program **SPECCOMB**. This step was necessary because during the stratification process, the Level_Two Class Maps lose the spatial structure associated with an image. The spatial structure is only maintained at Level_One and must be restored by using SPECCOMB.

3.2.4 Generating a CD Feature Map

Trials 1, 2, 3, and 9 tested the use of a PCS filter on the Standard TC transformed CD candidates for the Bayesian plus Unknown, Bayesian, Euclidean, and ISOCLASS classifiers, respectively. The mask generated from the Table 2 parameters was again used to stratify the May 1985 6-band image. In applying a PCS filter, the Level_Two Stratified May 1985 Multiband Scene was classified for each of the four classification methods. As before, only the changes were classified.

In the case of the Bayesian w/unknown class map, the unknown classes were given a different identifier. For May 1987, CV(UNKNOWN) = 25. For May 1985, CV(UNKNOWN) = 50.

In the case of ISOCLASS, the corresponding clusters for each date had to be identified using the program **DIVERGE**. During Trial 9, the distances between the clusters of one date with the clusters of the second date were compared. The smallest distances identified matching clusters. However, noting that the image clusters were collected exclusively from the stratified CHANGE image (regions with the highest potential for change), this matching process was judged to be risky. No other trials were made.

The PCS process was applied by using **ADDPIC** to subtract each May 1985 class map from the corresponding May 1987 class map. The resulting PCS images had a data type of INTEGER*2 with positive and negative integers. Because we are interested only in separating zero (no change) and non-zero values (change), the absolute value of these images was taken using the program **ABS**. Also, because the resulting image needs to be overlayed with the CD Feature Map (data type = BYTE), the images were then converted to data type BYTE using **CONVERT**.

3.3 Scene-Derived Brightness/Greenness Trials

Trials 15 and 16 performed a test of the Scene-Derived method for generating a CD mask. The May/May multiband scene pair was transformed, using the Gram-Schmidt Method for orthogonalizing vectors. The training set used for the transform were mean vectors taken from the 1985 and 1987 training set used for supervised classification. Three vectors were used to produce two brightness/greenness coefficients:

Training Vector	TC End Member
Water	Wet Soil
Bright Urban	Dry Soil
Deciduous Vegetation	Vegetation

Image-differencing and thresholding proceeded as described above, and Parametric Thresholding was used. The Bayesian w/Unknown and Bayesian classifiers were tested. Because of nearly equivalent results (to be discussed later), it was not necessary to test the PCS Filter Method.

3.4 Ground Truth Map

A ground truth map was made to represent 320 CHANGE and 17271 NO_CHANGE points for the purpose of generating contingency tables. These features are defined as follows:

> **Bright Urban:** Concrete or metal urban features such as concrete and metal rooftops, roads and runways. Also pure bright soil.
>
> **Mixed Urban:** A mixture of concrete and asphalt urban features, as well as construction areas.
>
> **Dark Road:** A specially selected dark paved road near airport in Frederick, MD.
>
> **No Change:** Areas that have not changed between May 1985 and May 1987.

Table 5 Summary List of CD Laboratory Trials

Trial #01	Filtered Bayesian w/ Unknown - May 85 to May 87 Parametric - Standard TC
Trial #02	Filtered Bayesian - May 85 to May 87 Parametric - Standard TC
Trial #03	Filtered Euclidean Distance - May 85 to May 87 Parametric - Standard TC
Trial #04	Unfiltered Bayesian w/Unknown - May 85 to May 87 Parametric - Standard TC
Trial #05	Unfiltered Bayesian - May 85 to May 87 Parametric - Standard TC
Trial #06	Unfiltered Euclidean Distance - May 1985 to May 1987 Parametric - Standard TC
Trial #07	Unfiltered ISOCLASS - May 1985 to May 1987 Parametric - Standard TC 5 change clusters
Trial #08	Unfiltered ISOCLASS - May 1985 to May 1987 Parametric - Standard TC - 5 change clusters combined from 10
Trial #09	Filtered ISOCLASS - May 1985 to May 1987 Nonparametric - Standard TC
Trial #10	Unfiltered Bayesian w/Unknown - May 85 to May 87 Nonparametric - Standard TC
Trial #11	Unfiltered Bayesian - May 85 to May 87 Nonparametric - Standard TC
Trial #12	Unfiltered Euclidean Distance - May 85 to May 87 Nonparametric - Standard TC
Trial #13	Unfiltered Bayesian w/ Unknown - Oct 85 to May 87 Parametric - Standard TC
Trial #14	Unfiltered Bayesian - Oct 85 to May 87 Parametric - Standard TC
Trial #15	Unfiltered Bayesian w/Unknown - May 85 to May 87 Parametric - Scene Derived TC
Trial #16	Unfiltered Bayesian - May 85 to May 87 Parametric - Scene Derived TC
Trial #17	Unfiltered ISOCLASS - May 1985 to May 1987 Parametric - Standard TC Water Included in Change Class of Trial #7
Trial #18	Unfiltered ISOCLASS - May 1985 to May 1987 Parametric - Standard TC Water Included in Change Class of Trial #8
Trial #19	Unfiltered ISOCLASS - May 85 to May 87 Parametric -Standard TC -Vegetation Masked
Trial #20	Unfiltered ISOCLASS - May 85 to May 87 Parametric - Standard TC - Vegetation Masked 4 clusters combined from 10

4.0 DISCUSSION OF RESULTS

Figures 4 and 5 show radiometrically enhanced color prints for a selected 512 * 512 subset of the May 1985 and May 1987 scenes, respectively. As with Figure 3, the RED-GREEN-BLUE band combination is B4-B7-B2. Figure 6 is a CD map for Trial 8, which was one of the better performing trials

A summary of the results of the 20 trials conducted during the experiment is shown in Figure 7. This figure contains plots of omission and commission errors versus the trial number for CHANGE and NO_CHANGE. The commission errors for CHANGE correspond to a false alarm rate for changes (also referred to earlier as a Type I error for the null hypothesis of NO_CHANGE). The omission errors for CHANGE correspond to missing known changes in the ground truth map. For the purpose of change detection, this omission error is the more serious of the two. The commission errors for NO_CHANGE correspond to labeling known changes as NO_CHANGE, whereas, the omission errors for NO_CHANGE correspond to labeling known non-changes as CHANGE.

The plots in Figure 7 were generated from the data found in Appendix D. This appendix contains the confusion matrices as well as the omission/commission errors for CHANGE and NO CHANGE for each trial in the experiment. The tables found in Appendix D group the cartographically significant changes (i.e., bright roofs, mixed urban, asphalt-predominant urban, and unknown) into a class called CHANGE, and the nonsignificant changes (i.e., vegetation and water) into a class called NO CHANGE.

A quick look at the 20 trials plotted in Figure 7 shows that these trials produced excellent omission and commission error rates for the NO_CHANGE category that ranged between 0.4 percent to 1.2 percent. Very acceptable omission error rates were demonstrated for the CHANGE category during some of the better performing trials that were as low as 2.2 percent (Trials 4, 5, 10, 11, 15, 16, 17, and 18). However, some of the trials (particularly those associated with the PCS filter) produced unacceptably high omission error rates -- as high as 39 percent. All of the trials produced somewhat high commission error rates for CHANGE that ranged from 21-41 percent.

A comparison of Trials 4 & 5 with Trials 15 & 16 indicates no significant difference between the results achieved from the standard TC method of generating the CD mask and the Scene-Derived method.

A comparison of Trials 4, 5, and 6 with Trials 10, 11 and 12 indicates that the results achieved from the parametric method of setting the mask thresholds were somewhat better than those achieved from the nonparametric method; however, this difference is probably not significant.

Trials 1, 2, 3, and 9 indicated difficulties with the PCS Filter Step. This step reduced the commission errors generated by the image differencing process; however, it also produced an unacceptable increase in the omission errors. For example, the omission error for the Bayesian classifier increased from 2.2 percent (Trial 5) to 39 percent (Trial 2). The increase in the omission error for the Bayesian w/ unknown classifier was only about half this amount -- increasing from 2.2 percent (Trial 4) to 23 percent (Trial 1).

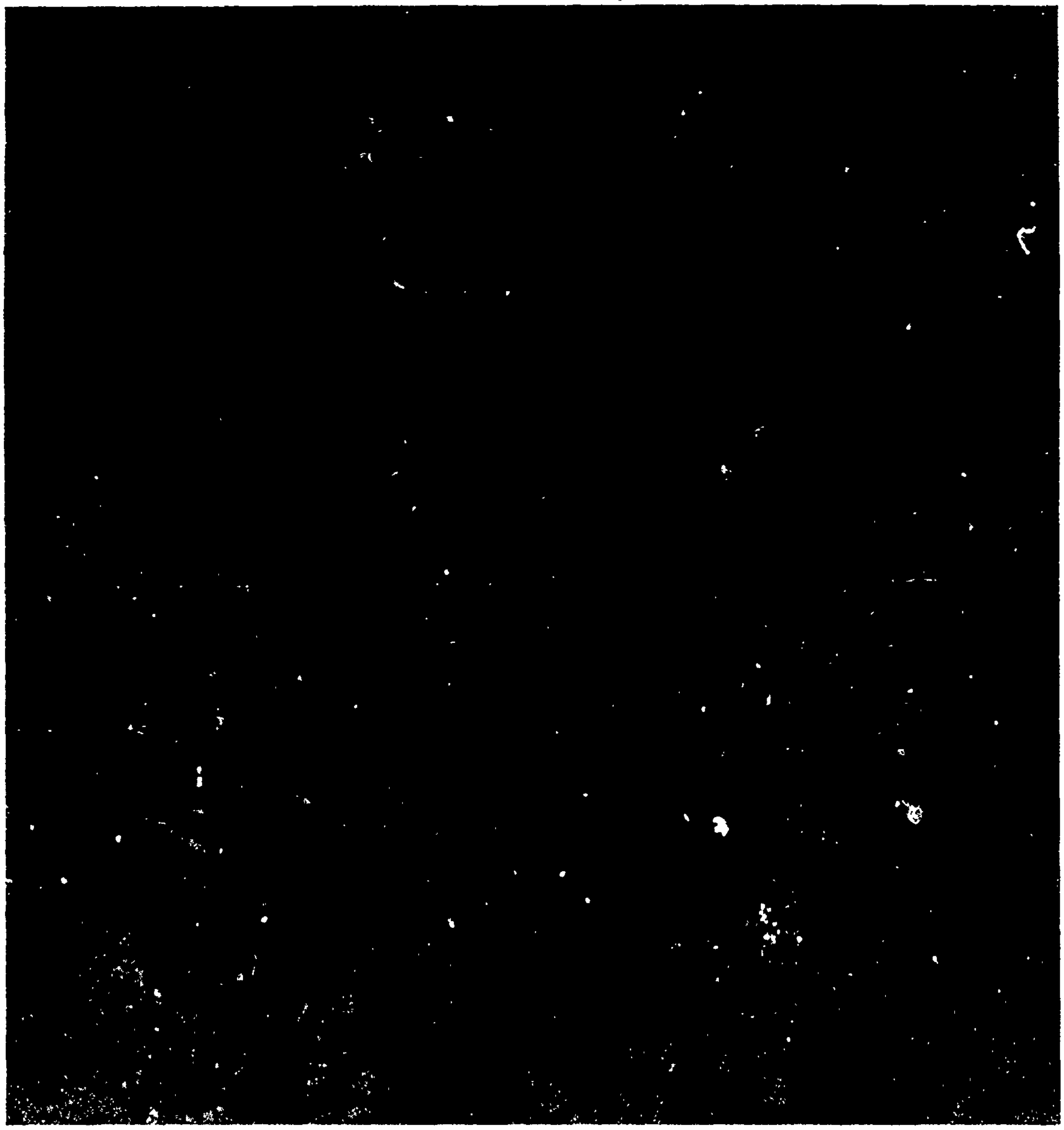


Figure 4. Radiometrically-Enhanced May 1985 Subset Scene (B4-B7-B2)

Figure 5. Radiometrically-Enhanced May 1987 Subset Scene (B4-B7-B2)

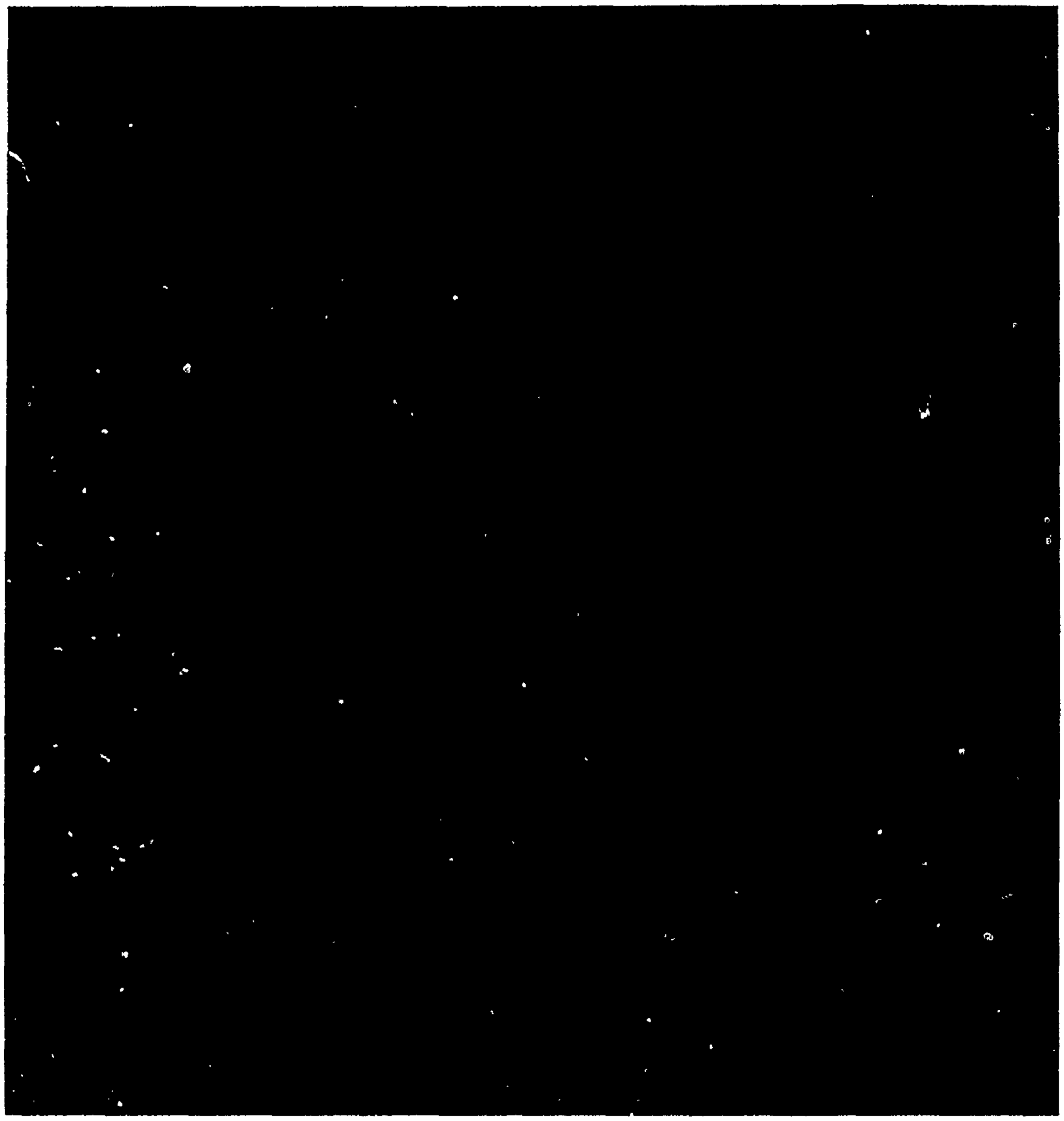
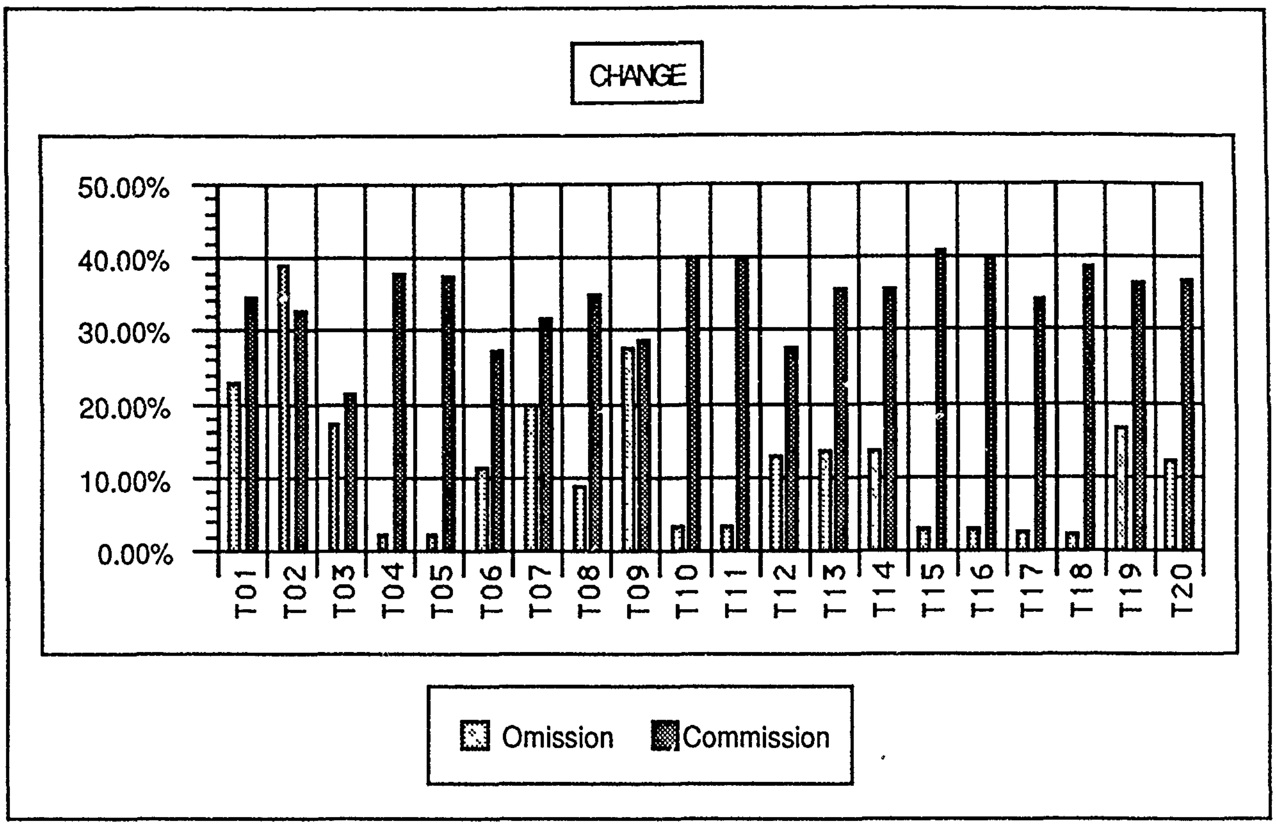


Figure 6. Class Map Results for Trial #8



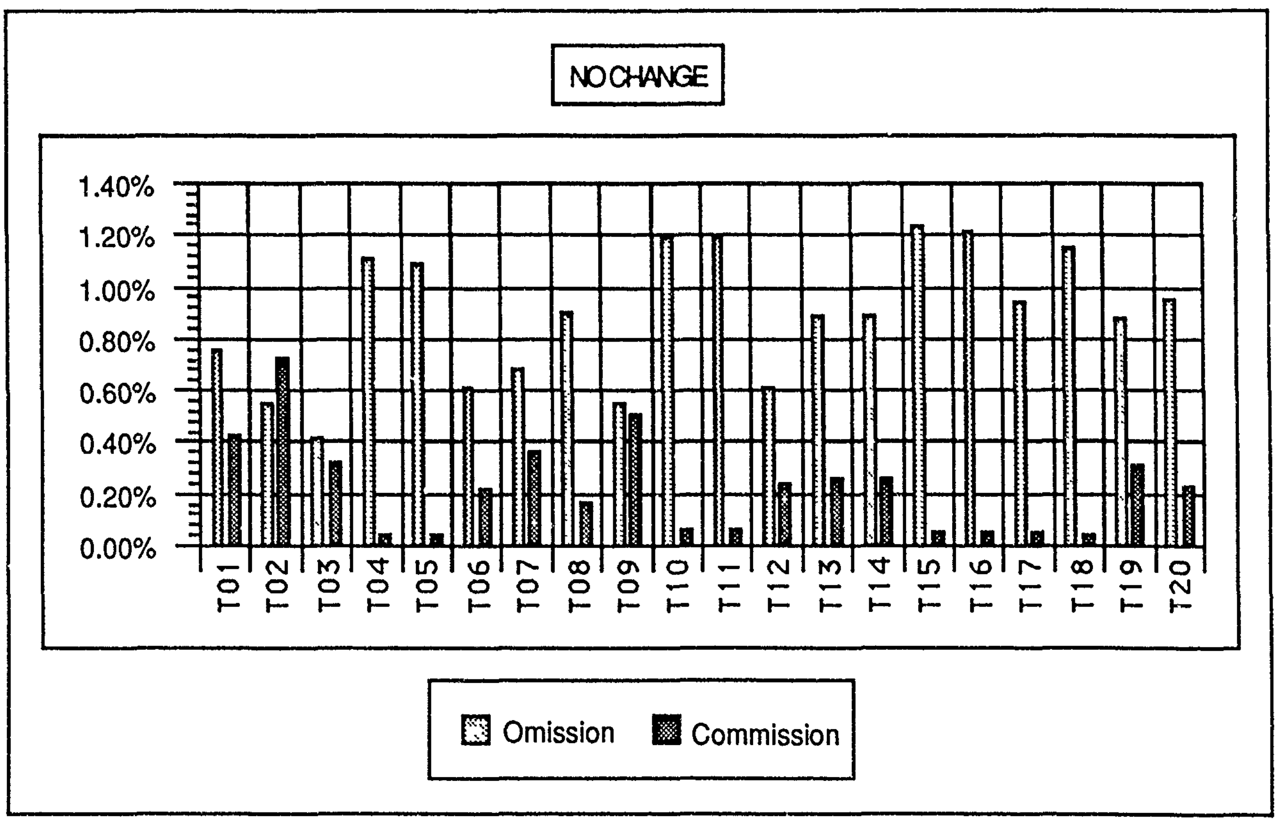


Figure 7. Plots of Omission and Commission Errors During 20 Trials for CHANGE and NO_CHANGE

Note that the problem in PCS performance can be reduced by labeling the filtered features as a separate FILTER class. An analyst could interactively focus attention on the features in this class to determine whether they have actually changed.

Further insight into the performance of the various clustering/classification operations can be gained by analyzing the confusion matrices found in Appendix E. The purpose of Trial 19 was to determine whether it is advisable to mask out vegetation prior to the classification stage.

A consistent problem for the classifiers occurred when separating water from asphalt-predominant urban features. This problem can be seen in Trial 7, where an ISOCLASS process using 5 clusters placed all of the 49 dark road pixels (in the ground truth map) into a water cluster. The confusion was reduced in Trial 8 by incorrectly placing 43 percent of these dark road pixels into the water class. Since this percentage was still an unacceptable error, the ISOCLASS process was invoked again, using a 15-cluster limit (results not shown). Although more clusters were generated, none helped to reduce this 43 percent error rate.

A likely source of ISOCLASS's difficulty could be in the default initial cluster assignments. Perhaps, if the mean vectors of the training classes (particularly, for water) were used as the initial seed points, ISOCLASS would have generated a cluster corresponding to water features.

The performance of ISOCLASS for identifying significant changes can be artificially improved if the definition of cartographic significant change is modified to include water. A comparison of the Figure 7 plots for Trials 7 and 8 with Trials 17 and 18 shows quite a drop in omission error. For example, comparing Trial 7 with 17 shows a drop in omission error from 19.7 percent to 2.5 percent.

Although it was not demonstrated in the confusion matrices, the supervised classifiers had another type of problem with water and asphalt-predominant urban classes. Visual inspection of the class maps generated by these classifiers showed an obvious confusion of the urban classes with water. Since water was not defined as a ground truth class, this problem was not quantified in the confusion matrices.

A comparison of the confusion matrices for Trials 7 and 19 shows that 32 of the 49 Dark Road features were incorrectly eliminated when using a different masking procedure. Since MV = {13, 23, 22, 33} was used to mask out vegetation, the values MV = 13, 23, 33 should be selectively eliminated from the mask to see if this problem can be isolated to a particular MV value.

5.0 CONCLUSIONS

In general, most of the pre-PCS (unfiltered) trials produced excellent omission and commission error rates (0.4 to 1.2 percent) for the NO_CHANGE category, and very good omission error rates (as low as 2.2 percent) for the CHANGE category. The excellent performance in some of these trials demonstrated that the first few steps of the methodology (up to the "Extract CD Feature Candidates" step) succeeded in extracting almost all the change in the scene.

The high commission error rates (21to 41 percent) for CHANGE emphasized the need to improve the subsequent classification and PSC filtering steps to eliminate false alarms. The PCS Filter Step reduced the commission errors generated by the image differencing process; however, it also produced an unacceptable increase in the omission errors. This performance problem can be reduced by labeling the filtered features as a separate FILTER class, and requiring the analyst to focus attention interactively on the features in this class to determine whether they have actually changed.

The high omission errors introduced by the PCS Filtering were not the fault of the approach, but rather they were due to the difficulties of conventional classifiers to accurately discriminate between different surface material types. Considering the discussion of Section 2.5.1, it is likely that that problems encountered in this step would be magnified greatly in CD methods that use classification methods for identifying CHANGE, rather than NO_CHANGE. Therefore, rather than alter the PCS Filtering approach (using classification as evidence for NO_CHANGE), efforts should be directed at improving the conventional classifiers and clustering methods.

Both the clustering operations and classifiers had difficulty separating water from asphalt-predominant urban features. The ISOCLASS algorithm tended to label water features as urban features; whereas, the Bayesian algorithm tended to label urban features as water. The Bayes confusion was not quantified in the confusion matrix results because water was not defined as a ground truth class.

A possible reason for ISOCLASS's difficulty in finding water could be in using the default initial cluster assignments. If the mean vectors of the training classes (particularly, for water) were used as the initial seed points, ISOCLASS might have generated a cluster corresponding to water features. This raises the issue of whether ISOCLASS should really be used in an unsupervised mode. It may be more suitable to use some of the clustering methods discussed in Section 2.4.3, such as Hybrid Search Clustering, Mixture Modeling, or graph-theoretic clustering.

No significant difference was found between the results achieved from the standard TC method of generating the CD mask and those obtained from the scene-derived method.

The results achieved from the parametric method of setting the mask thresholds were somewhat better than those achieved from the nonparametric method; however, this difference is probably not significant. Regardless, given its automation advantage and the fact that its performance is equal to or better than the nonparametric method, the parametric method is preferable.

6.0 RECOMMENDATIONS

I. Based on this report's conclusions, two implementations of the CD methodology should give adequate results for identifying cartographically significant change using Landsat TM. The steps for each method, along with the degree of automation for each step, are as follows:

Method 1 - Highly Automated:

1. Generate a registered pair of Standard TC Brightness/Greenness scenes (automated).
2. Subtract the Brightness/Greenness scene pair (automated).
3. By applying a parametrically derived threshold to the differenced scene pairs, generate a CD mask with nine values representing the increase/decrease/no_change combinations of brightness/greenness (automated).
4. Reduce the CD mask to two values representing CHANGE and NO_CHANGE (automated).
5. Stratify the most recent Landsat TM scene into CHANGE and NO_CHANGE multiband data using the two-value CD mask (automated).
6. Cluster the stratified CHANGE data using an unsupervised ISOCLASS algorithm with approximately 10 clusters (automated).
7. Group the clusters into significant and nonsignificant change (interactive).

Method 2 - Somewhat Automated:

1. Generate a registered pair of Standard TC Brightness/Greenness scenes (automated).
2. Subtract the Brightness/Greenness scene pair (automated).
3. By applying a parametrically derived threshold to the differenced scene pairs, generate a CD mask with nine values representing the increase/decrease/no_change combinations of brightness/greenness (automated).
4. Reduce the CD mask to two values representing CHANGE and NO_CHANGE (automated).
5. Define a set of training classes, consisting of sites that do not change between dates, using radiometrically enhanced color images (A color combination of Bands 4-7-2: Red, Green, Blue, is recommended). The ability to flicker registered color image pairs (before/after) on the same display is essential (interactive).
6. Stratify the most recent Landsat TM scene into CHANGE and NO_CHANGE multiband data using the two-value CD mask (automated).
7. Classify the stratified CHANGE data using a supervised classifier with an unknown class default (automated).
8. Stratify the older Landsat TM scene into CHANGE and NO_CHANGE multiband data using the two-value CD mask (automated).

9. Classify the older stratified CHANGE data using a supervised classifier with an unknown class default; label the unknown class differently than the one corresponding to the most recent date (automated).

10 Apply the PCS filter step which reduces commission error by tagging certain change pixels as FILTERED candidates (automated).

11 Interactively eliminate FILTERED candidates that the analyst determines have actually changed to reduce omission error (interactive).

II. These two methods should be tested for stability over a variety of scenes and dates.

III. The two methods should be compared to the performance achieved when using a CD mask obtained from differencing untransformed scene pairs.The methods should also be compared to the performance achieved when using a CD mask obtained from differencing other kinds of spectrally transformed scenes pairs. The use of characteristic vector transformations defined by linear discriminant functions should be investigated. The use of Common Principal Component Analysis (CPCA) should also be investigated.

IV. Although this study showed that the Scene-Derived method of generating the CD mask offered no advantage over the standard TC method for the scene pair tested, the use of the above two methods should be compared for other scene pairs (such as the Oct/May images).

V. Although the parametric method for defining thresholds produced acceptable results, further investigation into selecting an optimum threshold parameter and determining the stability of its performance over numerous scenes should be investigated.

VI. The effect of different initial cluster centers as input to ISOCLASS, as well as the overall stability of this clustering method, should be determined. The performance of ISOCLASS, when using the mean vectors of the training classes (particularly, for water) as the initial seed points, should be compared to the default unsupervised mode.

VII. Rather than alter the PCS Filtering approach (using classification as evidence for NO_CHANGE) in an attempt to improve the performance of the proposed Hybrid CD methodology, efforts should be directed at improving the conventional classifiers and clustering methods. The use of other clustering methods to replace ISOCLASS should be investigated. These include Hybrid Search Clustering, Mixture Modeling, and graph-theoretic clustering, as discussed in Section 2.4.3. Also, methods should be investigated that reduce the negative impact of mixed pixels. Such methods would need to incorporate spatial and spectral information about a pixel's neighborhood. Regression-based and probablistic relaxation-based techniques are good candidates. Accordingly, such new algorithms should be coded for testing, and the suitable ones installed as part of the LAS software.

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APPENDIX A - Properties of Spectral Transformations

This appendix begins by discussing some of the general and mathematical properties of a number of common spectral transformations. Since derivations are easily found in textbooks and community literature, they are referenced but not presented (i.e. refer to Seber for a formal treatment of linear modeling of multivariate normal data[18]). The second part of the appendix gives a simple graphic illustration of the standard TM Tasseled Cap Brightness/Greenness and the Scene-Derived Brightness/Greenness transformations.

Linear vs. Non Linear Transformations. The transformations considered in this study are all linear. The meaning of "linear" is that each transformed pixel vector y $\{y_i: i=1,m\}$ is related to the original pixel vector x $\{x_j: j=1,n\}$ by the linear matrix equation

$$y = Ax$$ where the components of the rectangular transformation matrix A are $\{a_{ij}: i=1,m \quad j=1,n\}$

In addition to being easy to compute, linear transformations have other desirable properties. It can be shown that if the feature vector x is multivariate normal, then the transformed feature vector y is multivariate normal with properties as follows

$$x \sim MVN(\mu, \Sigma)$$
$$y \sim MVN(A\mu, A\Sigma A^T)$$

where μ is the mean vector of x, Σ is the covariance matrix of x, and A as defined above.

The consequence of this property for feature extraction is that a linear transformation does not change the distributional property of the image data. If a classifier is designed to operate on normally distributed data (such as the conventional Maximum Likelihood Bayesian classifier), and the input image data is found to contain normally distributed class data, it is important to retain this statistical property through the transformation, otherwise, the classification results will be based on unsuitable assumptions, and yield poor results. This will undoubtedly happen if the transformation is non linear.

Independent Feature Components. Often it is desirable to have independent feature components. It can be shown that if x is MVN, then the components of x are independent, if, and only if, the covariance matrix Σ is diagonal. Since Σ is generally not diagonal, the strategy is often to find the transformation matrix A, such that $A\Sigma A^T$ is diagonal. Therefore, since y is MVN, such a transformation generates independent components. This strategy is used in a number of linear spectral transformations to generate independent components.

Note that this formulation of independence requires the assumption of normality. Most probably, an underlying flaw exists in the reasoning because the assumption of multivariate normality for the underlying population(s) is not usually true. One could use Σ (estimate of image covariance), Σ_i (estimate of covariance for class i), or pooled class covariances. The definition of independence is with respect to the population represented by covariance matrix being used (e.g. if Σ_i is used, independence is only defined with respect to class i).

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[18] G.A.F. Seber. *Linear Regression Analysis* New York, NY: John Wiley & Sons, 1977.

Reducing Correlation. One motivation for performing a spectral transformation is to reduce the correlation/covariance between bands. Intuitively, it would seem that the process of differencing a set of correlated bands, followed by logical "OR" combinations of masked correlated bands might not produce optimum results. Principal Component Analysis, also known as the **Karhunen-Loeve Transform (KLT)** is directed at reducing this correlation by performing operations on variance and covariance estimates of image data. These techniques are frequently used to reduce the number of bands based on the premise that small variance corresponds to little information. Therefore, transformed bands containing low overall variance are thrown away. However, correlation does not tell the entire story, and while such processes often work they are not reliable for feature extraction and CD.

Correlation vs Class Separability. The degree of correlation or the amount of variance can have little to due with class separability. A counterexample to show this fact is shown below in Figure A1. This figure shows how the KLT would transform the given data from [B1, B2] to [B1', B2']. Notice that the transformed band B1' containing the largest variance contains no information to separate the two classes, whereas the band containing the smallest variance B2' contains all this information.

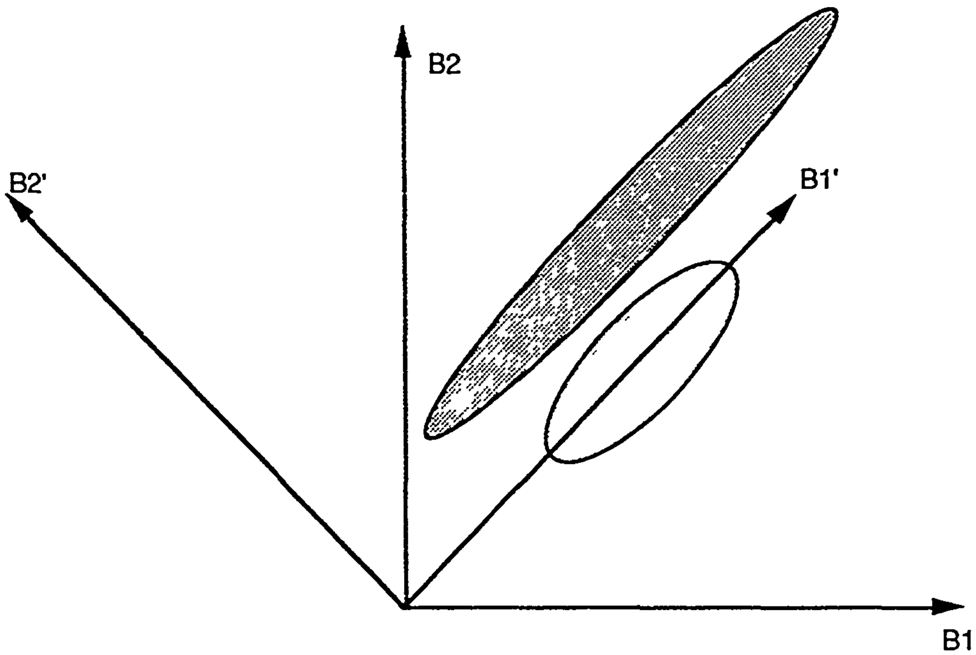

Figure A1. Class Distributions Leading to Poor Separability in KLT

The KLT, for example, is an optimal technique for minimizing the mean-square error criteria, but it is not optimized at all for class separability, and in fact does not even contain class covariance and variance information.

Either the Canonical Transform (CT) or the Common Principal Component Analysis (CPCA) for k-Groups should improve class separability because each uses class covariance information. For example, the CT maximizes interclass (between-class) variance and minimizes intraclass (within-class) variance. The CPCA finds a Maximum Likelihood estimate for a set of common principle axes that simultaneously diagonalizes all the class covariance matrices (see Flury).[19] However, both the CT and CPCA are linear transforms, and a linear mapping may not be sufficient to maximize class separability.

A nonlinear transformation method that attempts to reduce the dimensionality of a data set while preserving class separability was proposed by Koontz and Fukunaga.[20] This method is also discussed in Therrien.[21]

Characteristic Vector transformations. Rather than find a reduced set of transformed bands that optimize mean-square error or optimize class separability, another approach is to find a spectral transformation that generates bands which correspond to physically-meaningful features. For example, suppose a transformation could be found that generates an urban band, a vegetation band, and a water band; where bright pixels in the urban band correspond to features exhibiting a large degree of urbanness quality and dark pixels have no urbanness quality; where bright pixels in the vegetation band have a vegetative quality, etc.

The term "characteristic vector transformation" is introduced to categorize spectral transformations that are directed at generating such physically-meaningful bands. Intuitively, the differencing of physically-meaningful bands for CD would seem to make sense. For example, if the urbanness bands from two dates are subtracted, a large increase for a pixel corresponds to a significant increase in the urbanness of that feature and probably corresponds to a cartographically significant change.

For this study, the use of characteristic vector transformations are emphasized for CD. In particular, two kinds of characteristic vector techniques are considered: the standard TM Tasseled Cap Brightness/Greenness and the Scene-Derived Brightness/Greenness transformations.

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19 Flurry, Bernhard N. "Common Principal Components in k-Groups." *Journal of the American Statistical Association*, Vol. 79, Dec 1984: pp. 892-898.

20 Fukunaga K. and Koontz W.L.G. "A Nonlinear Feature Extraction Algorithm Using Distance Transformation." *IEEE Trans. Computers*, Vol. C-21, No. 1, 1972: pp. 56-63.

21 Therrien, Charles W. *Decision Estimation and Classification* (Section 5.7 Non-Linear Mapping). New York, NY: John Wiley & Sons,1989.

Brightness/Greenness. The differences between the standard TM Tasseled Cap brightness/greenness and the scene-derived brightness/greenness images reside in the transformation coefficients. Table A1 lists the standard Tasseled Cap coefficients as found in the literature[22], and the scene-derived coefficients as computed in this study for the May 1987 and May 1985 scenes. Figure A2 shows a plot of the brightness coefficients for the three transforms and a plot of the greenness coefficients. Note that large coefficients translate to large weights for the corresponding band in the original image, and small coefficients translate to small weights. Comparing the coefficients shows a similar trend for all three transformations for both brightness and greenness.

Table A1 Brightness/Greenness Transformation Coefficients

	Brightness Coefficients				Greenness Coefficients		
	TC B	MY87 B	MY85 B		TC G	MY87 G	MY85 G
Band 1	0.3037	0.395	0.3655	Band 1	-0.2848	-0.34	-0.3676
Band 2	0.2793	0.262	0.2511	Band 2	-0.2435	-0.189	-0.2158
Band 3	0.4743	0.4258	0.4134	Band 3	-0.5436	-0.3517	-0.3564
Band 4	0.5585	0.3477	0.3537	Band 4	0.7243	0.8277	0.80644
Band 5	0.5082	0.5929	0.6138	Band 5	0.084	0.1528	0.1573
Band 7	0.1863	0.3487	0.3614	Band 7	-0.18	-0.1287	-0.127

TC B:	Standard Tasseled Cap Brightness
MY87 B:	Scene Derived May 1987 Brightness
MY85 B:	Scene Derived May 1985 Brightness
TC G:	Standard Tasseled Cap Greenness
MY87 B:	Scene Derived May 1987 Greenness
MY85 B:	Scene Derived May 1985 Greenness

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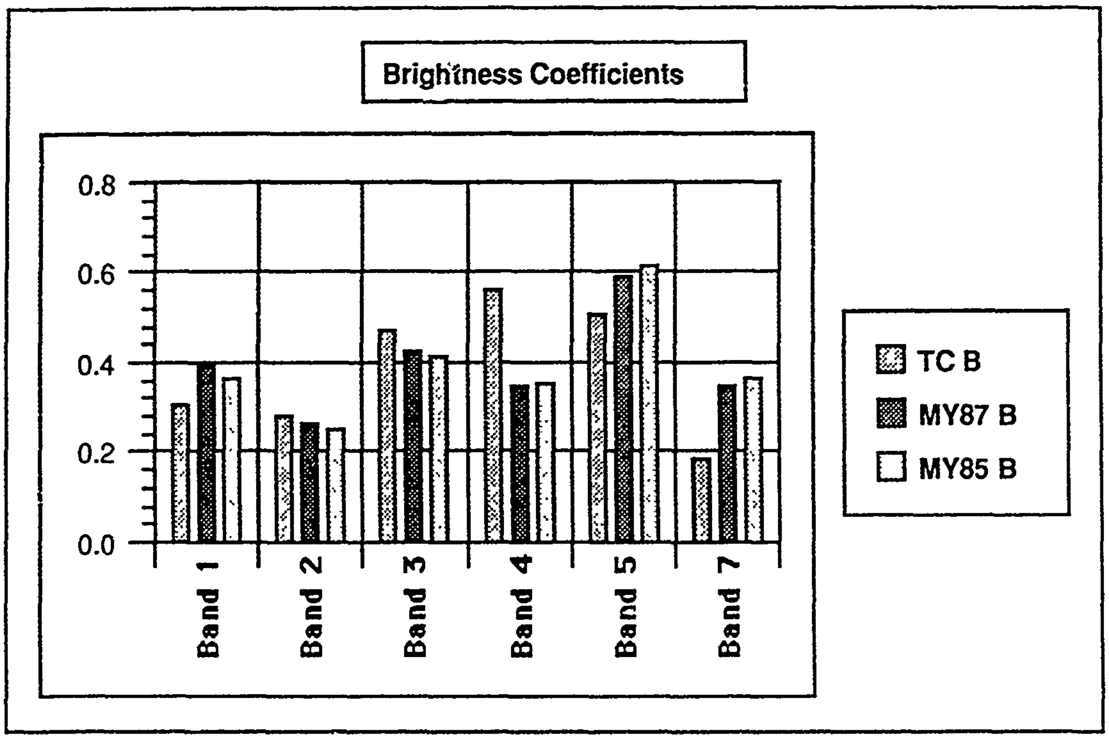
22 Crist, E.P. and Cicone, R.C.; "A Physically-Based Transformaton of Thematic Mapper Data - The TM Tasseled Cap." *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-22, May 1984: pp. 256-263.



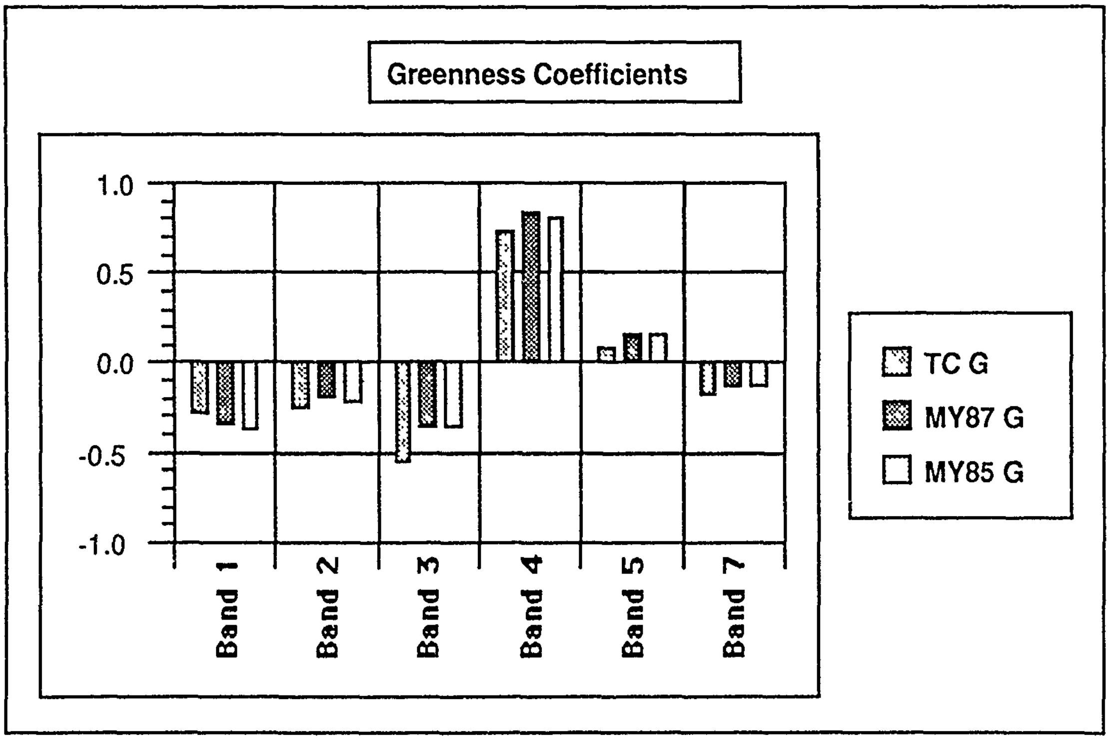


Figure A2. Plot of Standard TC and Scene Derived Brightness and Greenness Coefficients

APPENDIX B - Radiometric Image Enhancements

In order to view the brightness and greenness images on a display, the REAL**4 pixel values must be converted to a data type BYTE (8-bit integers). Rather than do this through an automatic conversion, better visual results are usually obtained if the conversion is done interactively in separate steps.

This process can be accomplished using the program **CONVERT** to first convert the REAL*4 data to INTEGER*2. At this point the images contain 16-bit positive and negative integers. The program **PIXCOUNT** is then used to generate a histogram. Breakpoints are selected from the histogram statistics which are used to define a multiple-point linear contrast stretch. A couple ways to define the breakpoints are given in Table B1

Table B1. Estimated Breakpoint Values for Piecewise Linear Contrast Stretch

Method 1 Percent Pixels/Bin	Method 2 Cumulative Percentage	Contrast Stretch Mapped Pixel Values
0.0%	0.0%	0
0.1%	0.5%	10
0.8%	5.0%	25
mode	50.0%	110
1.0%	95.0%	205
0.15%	99.5%	240
0.0%	100.0%	255

These breakpoints and corresponding contrast stretches are discussed in a USGS Reference manual for producing image maps.[23] According to this method, either the image's probability distribution or cumulative distribution histogram can be used to develop a piecewise linear contrast stretch of the pixel values. For the Probability Distribution method, the percent of pixels per histogram bin determines the breakpoint values for the contrast stretch. For the Cumulative Histogram method, the breakpoint values are determined by the cumulative percentage of the total number of pixels.

Once the breakpoints for a radiometric mapping are defined, **MAP** is used to apply the mapping and convert the INTEGER*2 data into BYTE data.

Note that the proposed CD methodology does not require viewing the spectrally transformed scene pairs. However, viewing these scenes does allow those interested to gain a better feel for what the Tasseled Cap transformation is doing. Also, a visual inspection helps to verify that the transformation procedure was implemented correctly.

23 "Procedure Manual for Preparation of Satellite Image Maps", Open File Report 86-19, Department of the Interior, U. S. Geological Survey, National Mapping Division.

APPENDIX C - Multispectral Training Classes

Mean vectors for the training classes of May 1987, May 1985, and October 1985 are listed in Table C1. A three dimensional spectral plot of the six training classes and the six Thematic Mapper Bands is shown in Figure C1. Spectral plots of the Bright Urban and Mixed Urban classes for three dates are shown in Figure C2.Spectral plots for the Deciduous and Coniferous Vegetation classes are shown in Figure C3.

Table C1 Mean Vectors for Training Classes

MAY 1987

	B1	B2	B3	B4	B5	B7
Bright Urban	200	110	154	117	183	107
Mixed Urban	121	52	64	59	75	43
Deciduous Vegetation	80	34	26	138	78	20
Water	82	31	27	13	6	3
Parking Lot	120	50	59	45	59	36
Coniferous Vegetation	83	33	30	73	63	23

MAY 1985

	B1	B2	B3	B4	B5	B7
Bright Urban	209	111	155	120	188	109
Mixed Urban	134	57	70	63	85	48
Deciduous Vegetation	91	34	29	145	82	21
Water	103	39	36	19	10	4
Parking Lot	128	50	56	42	51	31
Coniferous Vegetation	92	36	32	84	64	21

OCT 1985

	B1	B2	B3	B4	B5	B7
Bright Urban	147	79	109	83	132	76
Mixed Urban	87	36	42	37	49	27
Deciduous Vegetation	63	23	23	66	51	14
Water	67	25	23	9	4	1
Parking Lot	100	42	50	37	49	29
Coniferous Vegetation	62	22	20	44	34	11

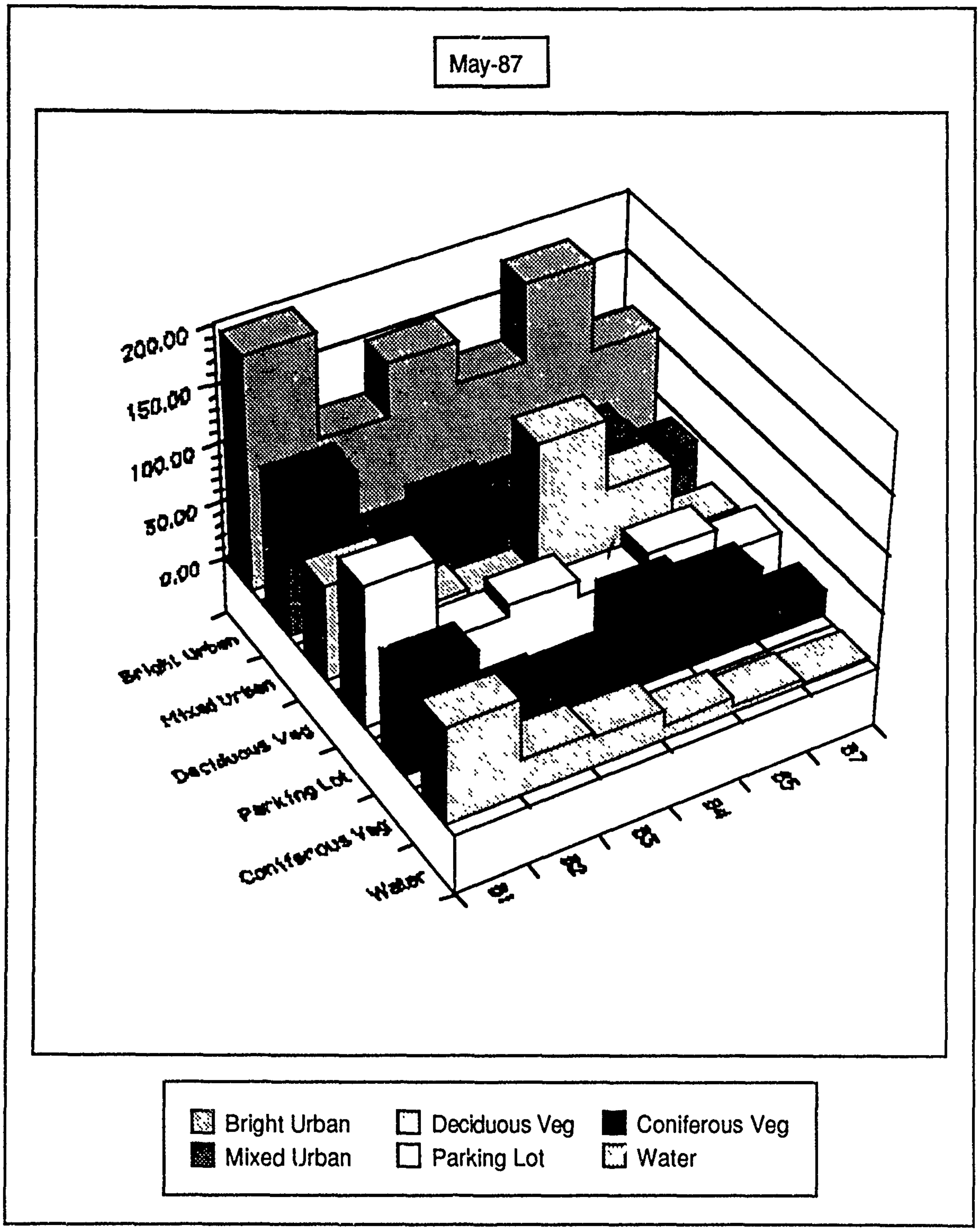


Figure C1. Three-Dimensional Spectral Plot of Training Classes

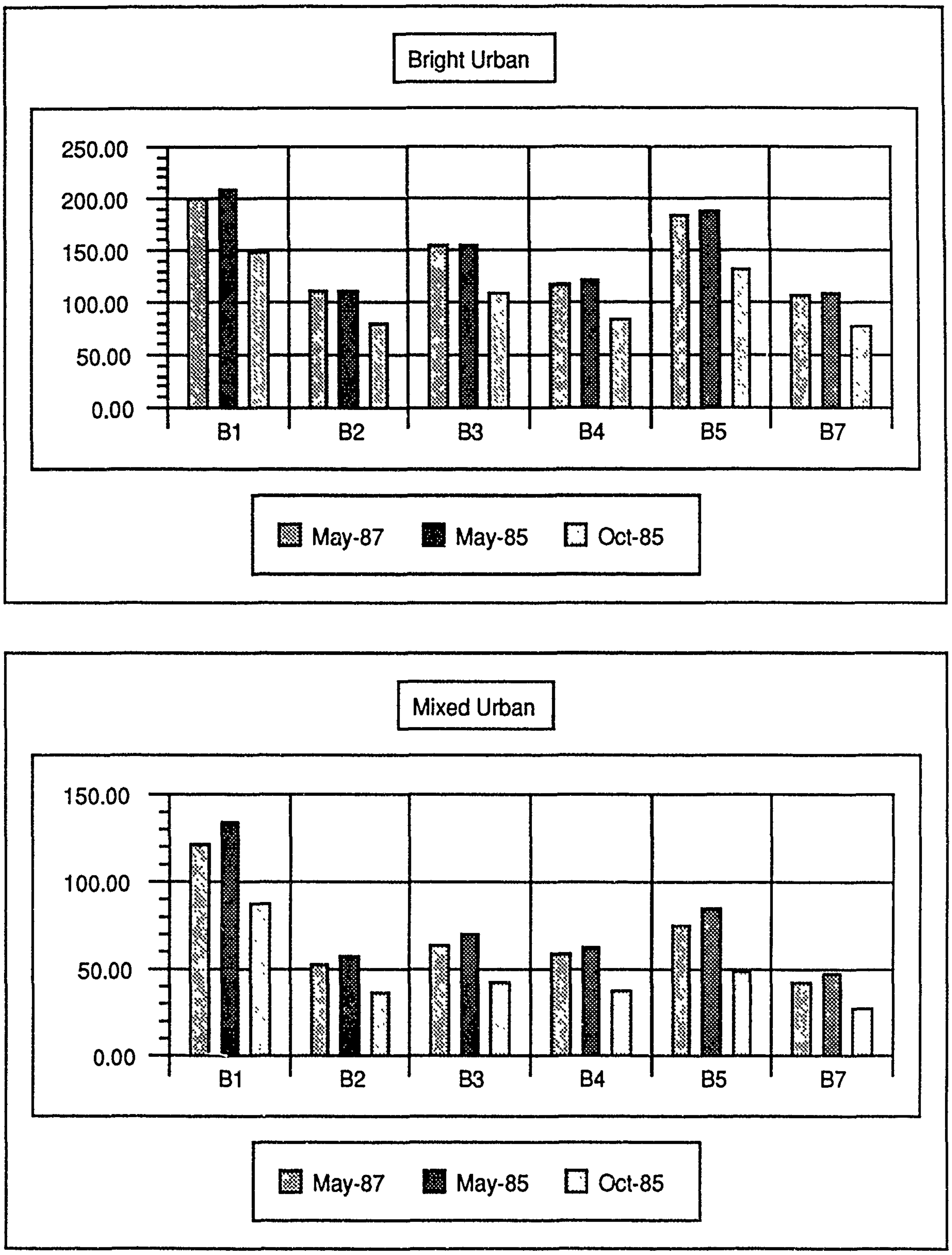


Figure C2. Spectral Plots of Bright Urban and Mixed Urban - 3 dates

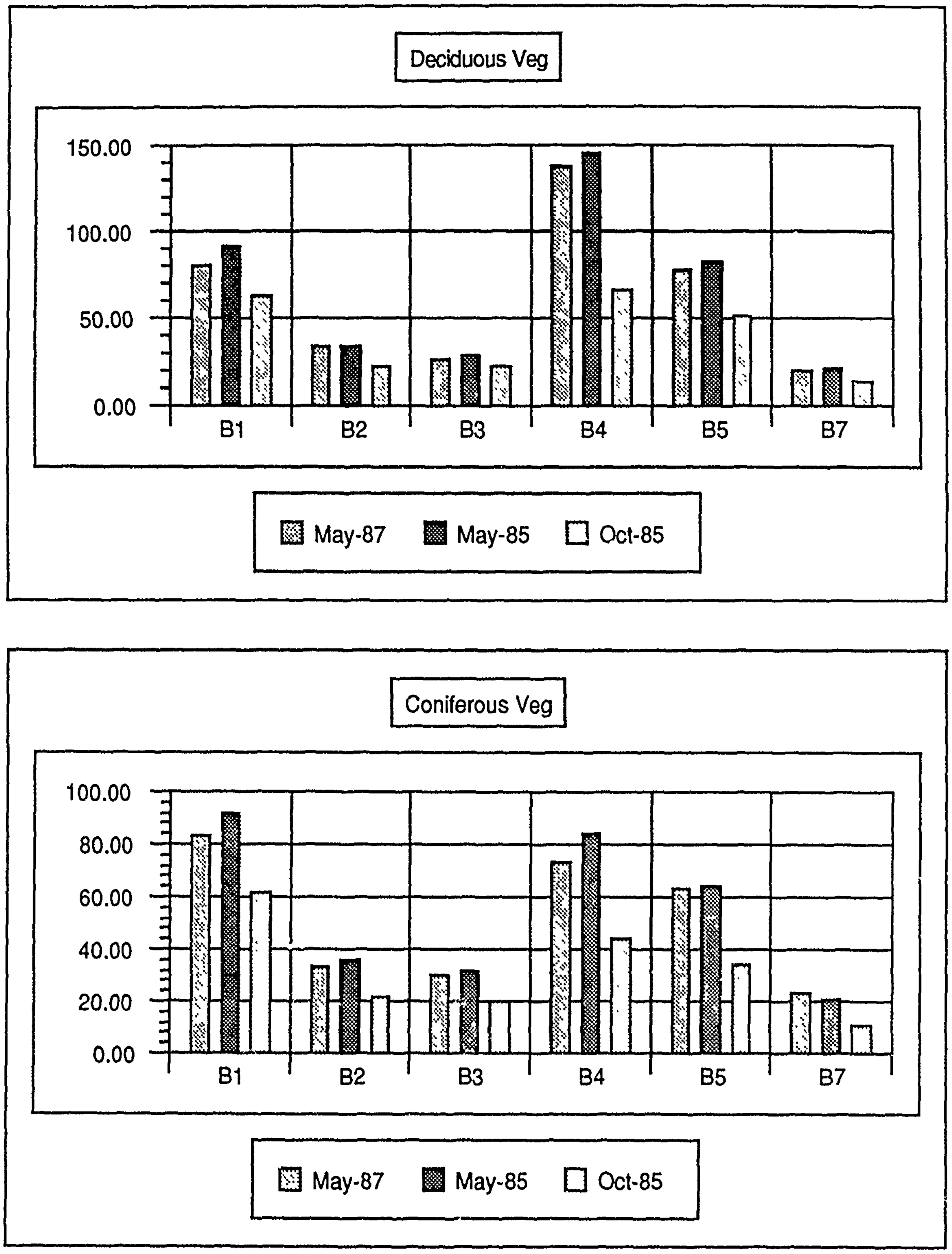


Figure C3. Spectral Plots of Deciduous and Coniferous Vegetation - 3 dates

APPENDIX D - Combined Results for CHANGE vs. NO_CHANGE

Table D1 lists the Change/No_Change results for the 20 trials. The matrices in this table have grouped the cartographically-significant changes (i.e. bright urban, mixed urban, mixed urban 2, parking lot, dark urban, and unknown) into a class called CHANGE, and the non-significant changes (i.e. vegetation and water) into a class called NO CHANGE. The combined (grouped) results were computed using the numerical class data in Appendix E.

A different grouping was made during Trials 17 and 18, where the water cluster was treated as a cartographically significant change. This grouping showed the significant improvement in CD results over corresponding Trials 7 and 8, where all else remained the same except for the treatment of the water cluster. The rationale behind doing this came from both analyzing the confusion matrices (in Appendix E) and visually inspecting various CD maps. The ISOCLASS algorithm experienced confusion separating the dark road (ground truth) feature from its water cluster. Although the supervised algorithms did not confuse urban areas with its water class, a visual inspection of these CD maps shows confusion between its urban class and water features that were not included in the ground truth map.

Each confusion matrix uses the first column to list the number of features labeled as CHANGE in the CD map that were identified in the ground truth map as CHANGE (row 1) and NO_CHANGE (row 2). The second column lists the number of features labeled as NO_CHANGE in the CD map that were identified in the ground truth map as CHANGE (row 1) and NO_CHANGE (row 2). Using the columns in this way, the CD map's commission errors can be computed.

An alternate way of reading the confusion matrix is to look at the first row as listing the number of features labeled as CHANGE in the ground truth map that were labeled as CHANGE (column 1) and NO_CHANGE (column 2) in the CD map, and the second row as listing the number of features that were labeled as NO_CHANGE in the ground truth map that were labeled as CHANGE (column 1) and NO_CHANGE (column 2) in the CD map. Using the rows in this way, the CD map's omission errors can be computed.

Table D1 Change/No Change Results

Trial #1
Filtered Bayesian w/ Unknown - May 85 to May 87
Parametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	247	73	320	Change	22.81%	34.66%
No Change	131	17140	17271	No Change	0.76%	0.42%
SUM	378	17213				

Trial #2
Filtered Bayesian - May 85 to May 87
Parametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	195	125	320	Change	39.06%	32.76%
No Change	95	17176	17271	No Change	0.55%	0.72%
SUM	290	17301				

Trial #3
Filtered Euclidean Distance - May 85 to May 87
Parametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	265	55	320	Change	17.19%	21.13%
No Change	71	17200	17271	No Change	0.41%	0.32%
SUM	336	17255				

Trial #4
Unfiltered Bayesian w/Unknown - May 85 to May 87
Parametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	313	7	320	Change	2.19%	38.02%
No Change	192	17079	17271	No Change	1.11%	0.04%
SUM	505	17086				

Trial #5
Unfiltered Bayesian - May 85 to May 87
Parametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	313	7	320	Change	2.19%	37.52%
No Change	188	17083	17271	No Change	1.09%	0.04%
SUM	501	17090				

Trial #6
Unfiltered Euclidean Distance - May 1985 to May 1987
Parametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	283	37	320	Change	11.56%	27.25%
No Change	106	17165	17271	No Change	0.61%	0.22%
SUM	389	17202				

Trial #7
Unfiltered ISOCLASS - May 1985 to May 1987
Parametric - Standard TC
5 change clusters

	Change	No Change	SUM		Omission	Commission
Change	257	63	320	Change	19.69%	31.47%
No Change	118	17153	17271	No Change	0.68%	0.37%
SUM	375	17216				

Trial #8
Unfiltered ISOCLASS - May 1985 to May 1987
Parametric - Standard TC
5 change clusters combined from 10

	Change	No Change	SUM		Omission	Commission
Change	292	28	320	Change	8.75%	34.82%
No Change	156	17115	17271	No Change	0.90%	0.16%
SUM	448	17143				

Trial #9
Filtered ISOCLASS - May 1985 to May 1987
Nonparametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	232	88	320	Change	27.50%	28.83%
No Change	94	17177	17271	No Change	0.54%	0.51%
SUM	326	17265				

Trial #10
Unfiltered Bayesian w/Unknown - May 85 to May 87
Nonparametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	309	11	320	Change	3.44%	40.00%
No Change	206	17065	17271	No Change	1.19%	0.06%
SUM	515	17076				

Trial #11
Unfiltered Bayesian - May 85 to May 87
Nonparametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	309	11	320	Change	3.44%	40.00%
No Change	206	17065	17271	No Change	1.19%	0.06%
SUM	515	17076				

Trial #12
Unfiltered Euclidean Distance - May 85 to May 87
Nonparametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	279	41	320	Change	12.81%	27.53%
No Change	106	17165	17271	No Change	0.61%	0.24%
SUM	385	17206				

Trial #13
Unfiltered Bayesian w/ Unknown - Oct 85 to May 87
Parametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	276	44	320	Change	13.75%	35.81%
No Change	154	17117	17271	No Change	0.89%	0.26%
SUM	430	17161				

Trial #14
Unfiltered Bayesian - Oct 85 to May 87
Parametric - Standard TC

	Change	No Change	SUM		Omission	Commission
Change	276	44	320	Change	13.75%	35.81%
No Change	154	17117	17271	No Change	0.89%	0.26%
SUM	430	17161				

Trial #15
Unfiltered Bayesian w/Unknown - May 85 to May 87
Parametric - Scene Derived TC

	Change	No Change	SUM		Omission	Commission
Change	311	9	320	Change	2.81%	40.65%
No Change	213	17058	17271	No Change	1.23%	0.05%
SUM	524	17067				

Trial #16
Unfiltered Bayesian - May 85 to May 87
Parametric - Scene Derived TC

	Change	No Change	SUM		Omission	Commission
Change	311	9	320	Change	2.81%	40.19%
No Change	209	17062	17271	No Change	1.21%	0.05%
SUM	520	17071				

Trial #17

Unfiltered ISOCLASS - May 1985 to May 1987
Parametric - Standard TC
5 change clusters
Water Included in Change Class of Trial #7

	Change	No Change	SUM		Omission	Commission
Change	312	8	320	Change	2.50%	34.32%
No Change	163	17108	17271	No Change	0.94%	0.05%
SUM	475	17116				

Trial # 18

Unfiltered ISOCLASS - May 1985 to May 1987
Parametric - Standard TC
5 change clusters combined from 10
Water Included in Change Class of Trial 8

	Change	No Change	SUM		Omission	Commission
Change	313	7	320	Change	2.19%	38.75%
No Change	198	17073	17271	No Change	1.15%	0.04%
SUM	511	17080				

Trial #19

Unfiltered ISOCLASS - May 85 to May 87
Parametric -Standard TC
Vegetation Masked

	Change	No Change	SUM		Omission	Commission
Change	267	53	320	Change	16.56%	36.28%
No Change	152	17119	17271	No Change	0.88%	0.31%
SUM	419	17172				

Trial #20

Unfiltered ISOCLASS - May 85 to May 87
Parametric - Standard TC
Vegetation Masked
4 clusters combined from 10

	Change	No Change	SUM		Omission	Commission
Change	281	39	320	Change	12.19%	36.85%
No Change	164	17107	17271	No Change	0.95%	0.23%
SUM	445	17146				

APPENDIX E - Confusion Matrix Class Results

Table E1 lists the confusion matrix results for the 20 trials with a breakdown into individual classes. These results were used to compute combined class results and commission/omission errors listed in Appendix D. The columns represent the change map features and the rows represent the Ground Truth Map features.

Reading down a column, the numbers for ground truth features (Bright Urban, Mixed Urban, Dark Road, and No Change) assigned to a particular change map category are listed. Commission errors can be computed for the various change map categories as the total number of incorrect ground truth features assigned to a particular change map category divided by the total number of features assigned to that category. For example, the commission error for "Mixed Urban" of Trial #1 is **CE(Mixed Urban)** = (19+ 92)/233 = 48%. Note that some of the change map categories do not have a corresponding ground truth category; therefore, commission errors for such classes do not make sense and cannot be computed.

Reading across a row, the numbers for Change Map features assigned to a particular ground truth feature are listed. Omission errors can be computed for the various ground truth features as the total number of incorrect change map features assigned to a particular ground truth category divided by the total number of features assigned to that ground category. As an example, the omission error for "Mixed Urban" of Trial #1 is **OE(Mixed Urban)** = (4 + 2 + 7 + 34 + 41)/ 210 = 42%.

Definition of Ground Truth Categories:

Bright Urban: Concrete or metal urban features such as concrete and metal rooftops, roads and runways. Also, pure bright soil.

Mixed Urban: A mixture of concrete and asphalt urban features, as well as construction areas.

Dark Road: A specially-selected dark paved road near airport in Frederick, MD.

No Change: Areas that have not changed between May 1985 and May 1987.

Definition of Change Map Features:

Bright Urban: Same as ground truth feature.

Mixed Urban: Same as ground truth feature.

Decid Veg: Deciduous Trees.

Water Class: Water class defined over sites of deep water selected for use in computing the scene-derived Brightness/Greenness transformation.

Parking Lot: Asphalt parking lot w/cars.

Conifer Veg: Coniferous Trees.

Water Cluster: Unsupervised cluster identified as water.

Table E1 Confusion Matrix Results

Trial #1
Filtered Bayesian w/ Unknown - May 85 to May 87
Parametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change	Filtered	Unk
Bright Urban	17	0	0	0	0	0	0	2	42
Mixed Urban	4	122	0	0	2	0	7	34	41
Dark Road	0	19	0	0	0	0	0	30	0
No Change	22	92	132	0	2	32	16911	65	15

Trial #2
Filtered Bayesian - May 85 to May 87
Parametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change	Filtered
Bright Urban	35	3	0	0	0	0	0	23
Mixed Urban	4	151	0	0	2	0	7	46
Dark Road	0	0	0	0	0	0	0	49
No Change	0	93	135	0	2	32	16911	98

Trial #3
Filtered Euclidean Distance - May 85 to May 87
Parametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change	Filtered
Bright Urban	56	0	0	0	0	0	0	5
Mixed Urban	24	164	0	0	1	1	7	13
Dark Road	0	9	0	0	11	29	0	0
No Change	1	64	134	3	6	45	16911	107

Trial #4

Unfiltered Bayesian w/Unknown - May 85 to May 87
Parametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change	Unk
Bright Urban	17	2	0	0	0	0	0	42
Mixed Urban	4	155	0	0	3	0	7	41
Dark Road	0	49	0	0	0	0	0	0
No Change	26	149	132	0	2	36	16911	15

Trial #5

Unfiltered Bayesian - May 85 to May 87
Parametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change
Bright Urban	35	26	0	0	0	0	0
Mixed Urban	4	196	0	0	3	0	7
Dark Road	0	49	0	0	0	0	0
No Change	28	158	135	0	2	37	16911

Trial #6

Unfiltered Euclidean Distance - May 1985 to May 1987
Parametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change
Bright Urban	61	0	0	0	0	0	0
Mixed Urban	24	176	0	0	2	1	7
Dark Road	0	9	0	0	11	29	0
No Change	30	70	206	3	6	45	16911

Trial #7
Unfiltered ISOCLASS - May 1985 to May 1987
Parametric - Standard TC
5 change clusters

	Bright Urban	Mixed Urban	Mixed Urban2	Veg	Water	No Change
Bright Urban	61	0	0	0	0	0
Mixed Urban	28	40	128	1	6	7
Dark Road	0	0	0	0	49	0
No Change	31	50	37	197	45	16911

Trial #8
Unfiltered ISOCLASS - May 1985 to May 1987
Parametric - Standard TC
5 change clusters combined from 10

	Bright Urban	Mixed Urban	Dark Urban	Veg	Water	No Change
Bright Urban	59	2	0	0	0	0
Mixed Urban	5	189	9	0	0	7
Dark Road	0	4	24	0	21	0
No Change	28	124	4	162	42	16911

Trial #9
Filtered ISOCLASS - May 1985 to May 1987
Nonparametric - Standard TC

	Bright Urban	Mixed Urban	Mixed Urban2	Veg	Water	No Change
Bright Urban	39	0	0	0	0	22
Mixed Urban	29	39	124	0	1	17
Dark Road	0	1	0	0	48	0
No Change	0	55	39	137	45	16995

Trial #10
Unfiltered Bayesian w/Unknown - May 85 to May 87
Nonparametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change	Unk
Bright Urban	17	2	0	0	0	0	0	42
Mixed Urban	4	148	0	0	3	0	11	44
Dark Road	0	49	0	0	0	0	0	0
No Change	27	174	135	0	2	45	16885	3

Trial #11
Unfiltered Bayesian - May 85 to May 87
Nonparametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change
Bright Urban	35	26	0	0	0	0	0
Mixed Urban	4	192	0	0	3	0	11
Dark Road	0	49	0	0	0	0	0
No Change	29	175	135	0	2	45	16885

Trial #12
Unfiltered Euclidean Distance - May 85 to May 87
Nonparametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change
Bright Urban	61	0	0	0	0	0	0
Mixed Urban	24	172	0	0	2	1	11
Dark Road	0	9	0	0	11	29	0
No Change	31	69	232	3	6	45	16885

Trial #13
Unfiltered Bayesian w/ Unknown - Oct 85 to May 87
Parametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change	Unk
Bright Urban	17	2	0	0	0	0	0	42
Mixed Urban	4	127	0	0	1	0	40	38
Dark Road	0	45	0	0	0	0	4	0
No Change	16	130	251	1815	3	6	15045	5

Trial #14
Unfiltered Bayesian - Oct 85 to May 87
Parametric - Standard TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change
Bright Urban	35	26	0	0	0	0	0
Mixed Urban	4	165	0	0	1	0	40
Dark Road	0	45	0	0	0	0	4
No Change	19	132	251	1815	3	6	15045

Trial #15
Unfiltered Bayesian w/Unknown - May 85 to May 87
Parametric - Scene Derived TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change	Unk
Bright Urban	17	2	0	0	0	0	0	42
Mixed Urban	4	153	0	0	3	0	9	41
Dark Road	0	49	0	0	0	0	0	0
No Change	25	169	132	0	2	50	16876	17

Trial #16

Unfiltered Bayesian - May 85 to May 87
Parametric - Scene Derived TC

	Bright Urban	Mixed Urban	Decid Veg	Water	Parking Lot	Conifer Veg	No Change
Bright Urban	35	26	0	0	0	0	0
Mixed Urban	4	194	0	0	3	0	9
Dark Road	0	49	0	0	0	0	0
No Change	27	180	135	0	2	51	16876

Trial #17

Unfiltered ISOCLASS - May 1985 to May 1987
Parametric - Standard TC
5 change clusters
Water to be Included in Change Class of Trial #7

	Bright Urban	Mixed Urban	Mixed Urban2	Veg	Water	No Change
Bright Urban	61	0	0	0	0	0
Mixed Urban	28	40	128	1	6	7
Dark Road	0	0	0	0	49	0
No Change	31	50	37	197	45	16911

Trial # 18

Unfiltered ISOCLASS - May 1985 to May 1987
Parametric - Standard TC
5 change clusters combined from 10
Water to be Included in Change Class of Trial 8

	Bright Urban	Mixed Urban	Mixed Urban2	Veg	Water	No Change
Bright Urban	59	2	0	0	0	0
Mixed Urban	5	189	9	0	0	7
Dark Roads	0	4	24	0	21	0
No Change	28	124	4	162	42	16911

Trial #19

Unfiltered ISOCLASS - May 85 to May 87
Parametric -Standard TC
Vegetation Masked

	Bright Urban	Mixed Urban	Mixed Urban2	Mixed Urban3	Water	No Change
Bright Urban	60	1	0	0	0	0
Mixed Urban	15	116	25	47	0	7
Dark Road	0	0	3	0	14	32
No Change	30	29	85	8	43	17076

Trial #20

Unfiltered ISOCLASS - May 85 to May 87
Parametric - Standard TC
Vegetation Masked
4 clusters combined from 10

	Bright Urban	Mixed Urban	Dark Urban	Water	No Change
Bright Urban	57	4	0	0	0
Mixed Urban	4	189	10	0	7
Dark Road	0	6	11	0	32
No Change	18	142	4	31	17076