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A Comparative Analysis of Spectral Band Selection Techniques

M.S. Thesis

by

Julia M. Laurenzano
Captain, USAF

B.S. Duke University
(1994)

Rochester Institute of Technology
Chester F. Carlson Center for Imaging Science

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(93 pages)

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requirements for the degree of Master of Science
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M.S. DEGREE THESIS

The M.S. Degree Thesis of Julia M. Laurenzano
has been examined and approved by the
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Date

1.0 Abstract

The ability to determine optimal spectral band sets for the exploitation of multispectral and hyperspectral imagery is of great concern due to data transfer, storage, and computational constraints. This study compares the performance of three band selection techniques across a range of scenarios and image exploitation algorithms. Thresholded Divergence, a technique based on Gaussian Maximum Likelihood classification, Forward Sequential Band Selection, an iterative method based on target identification algorithms, and Spectral Basis Functions, a method independent of end-exploitation, were selected for evaluation. Each of these band selection techniques was applied to two M7 multispectral images and two HYDICE hyperspectral images. Each selected optimal spectral band set for each image was classified and assessed for classification accuracy. Comparisons between band selection techniques were made based on spectral band subset size, image exploitation algorithm, image and scene type, and input parameter set.

Acknowledgments

I would like to thank the many people whose combined efforts have made this study possible: Dr. John Schott, my thesis advisor, for his steady guidance and feedback; Rolando Raqueno for diverting numerous coding-related crises at a moment's notice; Major Ron Fairbanks for his continual support as study partner as an admirable officer; Captain Chaz Daly for his injection of humor and optimism at just the right time; Jackie Patterson for providing perspective, and the many people from Eastman Kodak who introduced me to and challenged me with countless new ideas.

Most importantly, I would like to thank my parents for their unconditional love and support.

Dedication

This thesis is dedicated to Beth and Trish who embody the meaning of friendship. You are my sisters.

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2.0 Introduction and Summary

Multispectral imagery has become much more important due to the increase in the number of spectral bands in available imagery. Hyperspectral sensors such as NASA's Advanced Visible and Infrared Imaging Spectrometer (AVIRIS) have hundreds of channels over a wide spectral range. While such technological advances have greatly enhanced the contributions of remote sensing, the associated increase in data is accompanied by subsequent time, cost, and storage considerations. In the case of multispectral image classification, more basic techniques, such as minimum distance to the mean exhibit a linear relationship between number of spectral bands and increase in cost. The same relationship for more statistically intensive, and typically more accurate, techniques such as Gaussian Maximum Likelihood (GML) are quadratic in nature (Richards, 1993). For example, a 210-band Hyperspectral Digital Imagery Collection Experiment (HYDICE) image with 320 samples and 960 lines requires over 64 Mbyte for image transfer and storage. The same file using only 4 of the available 210 spectral bands would require only 1.2 Mbyte. If equivalent exploitation accuracy levels could be achieved for that same image using only 4 spectral bands, the transfer and storage requirements would be reduced by a factor of nearly 6, while the cost of GML classification would be reduced by a factor of 10^4. Clearly, it would be advantageous to be able to collect data using only those spectral bands containing useful information for image classification in order to minimize cost.

For this reason, numerous techniques have emerged to predetermine which spectral bands produce optimal classification results. Csillag, *et al.* (1992) presented a modified stepwise principal component analysis for the determination of key spectral ranges for the identification of soil salinity status. Mausel, *et al.* (1990), Schott, *et al.* (1988), and

Rosenblum (1990) used assorted Bayesian statistical techniques to predict optimal spectral band combinations for use with Gaussian Maximum Likelihood classification. Similar statistical methods were used by Kanodia, *et al.* (1996) and Hardie (1994) to select optimal spectral bands for use with hypothesis testing and Signal-to-Clutter target identification techniques. Thomas (1994) elaborated on these techniques in his development of a Signal-to-Clutter ratio score for selecting spectral bands to use in target identification. Price (1994) demonstrated an interactive method for selecting bands using a set of basis functions. For the most part, these studies have been fairly limited in scope in that each technique is geared towards a specific image type or classification algorithm.

In addition, in many cases the specific scenario class statistics or post-processing algorithm are not known *a priori*. The aforementioned algorithms, then, may be of limited value for predetermining optimal spectral band sets. With this in mind, this study will focus on the implementation of Thresholded Divergence, Spectral Basis Function, and Forward Sequential Band Selection optimal spectral band selection techniques across multiple scenarios and multiple classification algorithms. Each of the band-selection algorithms was developed under the Environment for Visualizing Information (ENVI™) using the Interactive Display Language (IDL™) Once the optimal spectral bands were selected, the lower-dimensional images were classified using Gaussian Maximum Likelihood (GML), Signal-to-Clutter Ratio, and Log-Likelihood Ratio classification algorithms. Of the aforementioned classifiers, GML was run using existing applications under ENVI™. Both the Signal-to-Clutter Ratio and Log-Likelihood Ratio classifiers were developed under ENVI™ in the course of this research. Finally, the classification accuracies of each band-selection technique was evaluated. GML results were evaluated using independent analysis and stratified random-sampling confusion matrices. The

Signal-to-Clutter and Log-Likelihood results were evaluated using receiver operating characterization (ROC) curves. All of the evaluation methods were developed within the ENVI™ environment. This assessment will determine if any one band selection method proves more effective than its counterparts across the selected range of scenarios and exploitation algorithms. Comparisons will be made between band selection techniques based on image type, classification method, and input parameter combination.

3.0 Objectives and Deliverables

Statement of Work

- Construct a robust data set incorporating two (2) M7 images and two (2) HYDICE images.
- Develop and implement the necessary band selection algorithms, classifiers, and accuracy assessment metrics in the Environment for Visualizing Information (ENVI™) and the Advanced Visualization System (AVS).
- Construct common training sets to be used by all band selectors, classifiers, and accuracy assessment metrics.
- Reduce initial image spectral band sets using Eigenvector Pre-Selection, Thresholded Divergence, Forward Sequential Band Selection, and Spectral Basis Functions for a range of input parameter sets.
- Classify each image using the down-selected spectral band sets using common training data and the Gaussian Maximum Likelihood, Signal-to-Clutter Ratio, and Log-Likelihood Ratio classifiers.
- Generate confusion matrices for the Gaussian Maximum Likelihood classifier outputs. Analyze confusion matrices based on simple accuracy.
- Generate ROC curves for the Signal-to-Clutter Ratio and Log-Likelihood Ratio classifier outputs. Analyze ROC curves based on the summed difference between probability of detection and probability of false alarm.
- Generate confusion matrices and ROC for top performing spectral band subsets using stratified random sampling.
- Comparatively evaluate the band selection algorithms based on accuracy assessment results.

List of Deliverables

- The following band selection algorithms developed under ENVI™:
    - Thresholded Divergence
    - Spectral Basis Functions
    - Forward Sequential Band Selection
- The following classification algorithms developed under ENVI™:
    - Signal-to-Clutter Ratio
    - Log-Likelihood Test Ratio
- Accuracy assessment metric developed under ENVI™
    - Independent analysis confusion matrix
    - Stratified random sampling confusion matrix
    - Independent analysis receiver operating (ROC) curves
    - Stratified random sampling ROC curves
- A written document detailing the spectral band selection techniques and their relative value across a range of images and exploitation algorithms.

4.0 Background

4.1 Optimal Band Selection

Image collection using an increasing number of spectral bands has naturally resulted in much greater quantities of data to be processed and analyzed. While computational abilities have improved substantially in recent years, computational time and accuracy concerns continue to steer sensor and algorithm development. Sensor research and development would benefit immensely from reduced computational time and subsequent cost if the spectral bands which would provide optimal imagery for a specified application and /or scene could be known in advance. The goal thus far has been to select the subset of k bands from the total set of N bands (where $k < N$) such that the classification results do not suffer degradation. (Rosenblum, 1990)

A number of methods have been investigated with this end in mind. One of the earliest techniques, known as Principal Components Analysis (Schowengerdt, 1983), is based on the understanding that not all of the output multispectral image data necessarily contain useful information. The principal components technique transforms the multispectral data into a coordinate space with orthogonal axes that are uncorrelated and ordered according to decreasing variance. Since only those transformed bands with higher levels of data variance are usually useful for classification, the amount of data is reduced to a limited number of transformed bands which maximize the data. While this technique is well known, Schott *et al.* (1988) suggests that its nature as a post-acquisition tool prohibits its use as a preliminary band selection tool.

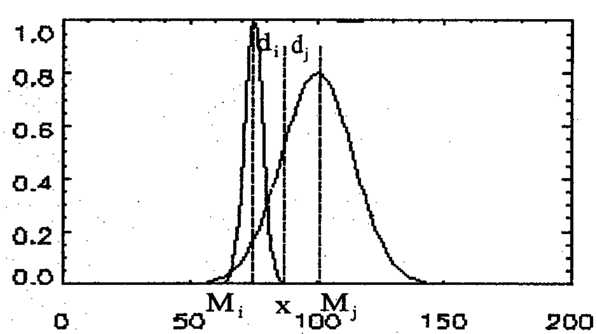
4.1.1 Class Separation Matrix

Schott, *et al.* (1988) developed a technique in which a class separation matrix is used to determine optimal spectral bands. The metric is:

$$Z=[\sum_{j=1}^{k}\sum_{l=1}^{k} w_{ij}d_{ij}]^{1/2} \quad \textbf{(1)}$$

where d_{ij} is the Mahalanobis distance of class j from class i and w_{ij} is the weight factor. A geometrical representation of the Mahalanobis distance is shown in Figure (1); the mathematics are discussed more thoroughly in Section (4.2.1). In Figure (1), M_i and M_j are the mean vectors for class i and class j, x is the pixel column vector, and d_i and d_j are the multivariate distances between the pixel column vector and the class means. In general w was set to 1 for distances between target and background classes, and set to 0 for distances between backgrounds. The k bands resulting in a maximum value for Z are

Figure 1: Geometrical Representation of the Mahalanobis Distance



deemed optimal. This metric was designed specifically for use in conjunction with the GML classifier.

4.1.2 Divergence, Transformed Divergence (TD), Bhattacharyya Distance (B distance), and Jeffries-Matusita Distance (JM)

Mausel, *et al.* (1990) compares several techniques for optimal spectral band selection for classification purposesh. Divergence, Transformed Divergence (TD), Bhattacharyya Distance (B distance), and Jeffries-Matusita Distance (JM) were selected based on their demonstrated abilities to select subsets of spectral bands from multidimensional data resulting in reasonable classification results using the GML classifier.

Divergence as presented in Richards (1993) assumes that the class means and covariances are normally distributed. The measure of divergence is written:

$$d_{ij}=\frac{1}{2}Tr[(\Sigma_i-\Sigma_j)(\Sigma_j^{-1}-\Sigma_i^{-1})]+\frac{1}{2}Tr[(\Sigma_j^{-1}+\Sigma_i^{-1})(\mu_i-\mu_j)(\mu_i-\mu_j)^t] \tag{2}$$

where Σ is the class covariance matrix, μ is the class mean vector, and Tr is the trace of the matrix. The sum of the divergences for all possible class pairs is presented in Rosenblum (1990) as the overall divergence; the set of spectral bands which maximized the overall divergence should represent the greatest class separability and, therefore, the best classification accuracy. A problem arises with divergence as a means of band selection because of its nonlinear relationship to classification accuracy. Richards (1993) demonstrates that divergence increases as a quadratic function of separation between multispectral classes; a small increase in separation between classes which are already distant will result in a substantial increase in divergence which does not necessarily correspond to the relative change in classification accuracy.

A modification known as the Transformed Divergence atones for this problem. Defined as:

$$d_{ij}^{T}=2(1-e^{-d_{ij}/8}) \tag{3}$$

the exponential results in asymptotic behavior as opposed to the quadratically increasing behavior demonstrated by divergence.

A second distance measurement used for spectral band selection is known as the Bhattacharyya Distance. Similarly based on the multi-dimensional distance between two classes, the B-distance is written:

$$B_{ij}=\frac{1}{8}(\mu_i-\mu_j)^T\left(\frac{\Sigma_i+\Sigma_j}{2}\right)^{-1}(\mu_i-\mu_j)+\frac{1}{2}\ln\frac{\left|\frac{\Sigma_i+\Sigma_j}{2}\right|}{\sqrt{|\Sigma_i||\Sigma_j|}} \tag{4}$$

where once again Σ is the class covariance matrix and μ is the class mean vector. A manipulation similar to that used above with divergence yields the Jeffries-Matusita Distance :

$$J_{ij}=[2(1-e^{-B_{ij}})] \tag{5}$$

The comparative analysis presented in Mausel, *et al.* (1990) was based on classification accuracies using data from the four best spectral bands selected by Divergence, TD, B-distance, and JM. The analysis revealed that, while Divergence and B-distance provide more precise statistical distances between the classes, TD and JM result in substantially better spectral band selection based on GML classification accuracies. One additional point of interest raised by Richards (1993) is that TD is much less computationally intensive and, therefore, more cost effective than the slightly more accurate JM.

Each of the four techniques studied by Mausel, *et al.* (1990), requires the same number of calculations:

$$calculations = \frac{N!}{k!(N-k)!}\frac{M!}{2!(M-2)!} \tag{6}$$

where N is the total number of bands, M is the number of classes in the image, and k is the number of spectral bands in the desired subset.

4.1.3 Thresholded Divergence

In her work, Rosenblum (1990) expanded upon the aforementioned concepts to develop a technique specifically intended for feature selection. Beginning with the conditional probability similar to that used in Gaussian Maximum Likelihood (GML) classification:

$$p(M_j|i) = \frac{1}{(2\pi)^{j/2}|\sum_i|^{1/2}} e^{[-\frac{1}{2}(M_j-M_i)^T\sum_i^{-1}(M_j-M_i)]} \tag{7}$$

where Σ_i is the covariance matrix and $\mathbf{M_j}$ and $\mathbf{M_i}$ are the multivariate class mean vectors, we can take the natural logarithm and add $\ln|\Sigma_i|$ to both sides such that:

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where Σ_i is the covariance matrix and $\mathbf{M_j}$ and $\mathbf{M_i}$ are the multivariate class mean vectors, we can take the natural logarithm and add $\ln|\Sigma_i|$ to both sides such that:

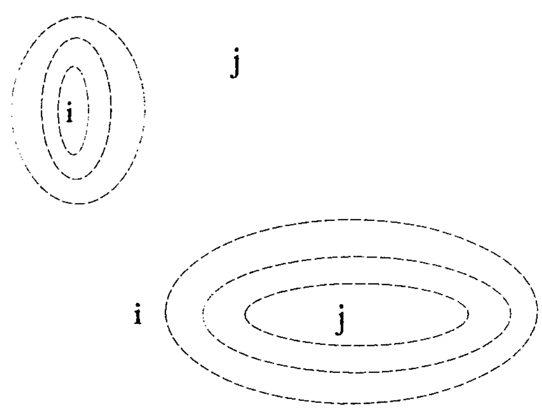
$$D_i + \ln|\textstyle\sum_i| = -2\ln\left[\frac{P(M_j|i)}{(2\pi)^{j/2}}\right] \tag{8}$$

where

$$D_i = (M_j - M_i)^T \textstyle\sum^{-1} (M_j - M_i) \tag{9}$$

The quantity on the left side of equation (8) is the measured distance between two class means when individual class covariances are used. Figure (2) illustrates how the distance from i to j will not be the same as the distance from j to i in probability space when the

Figure 2: Statistical Distance Between Class Means



covariance matrix from class j is used. The dimensions of each ellipse in Figure (2) depend on the class variance from which the statistical distances are measured. Based on the ellipses shown, the variance for class i is considerably smaller than that of class j.

Thus, the distance measurement between class *i* and class *j* based on the variance in class *i* is larger than the distance measurement based on the variance in class *j*.

The right side of equation (8) defines the necessary separation distance between two class means for a probability of misclassification $P(\mathbf{M}_j|i)$. A threshold is defined using equation (10):

$$d_{thresh} = -2\ln\left(\frac{P(M_j|i)}{(2\pi)^{j/2}}\right) \tag{10}$$

If the measured distance ($D_i + \ln|\Sigma_i|$) between two class means is greater than d_{thresh}, the distance is sufficient for reasonable classification accuracies. Finally, a ratio is computed to prevent inflation of the sum of all distances between classes:

$$d_{ratio} = \frac{D_i + \ln|\sum_i|}{d_{thresh}} \tag{11}$$

in which values for d_{ratio} greater than 1 are set equal to 1.

The ratio of thresholded distances between all classes for a specified subset of features form a matrix

$$D_r = \begin{pmatrix} d_{r11} & d_{r12} & \cdots & d_{r1i} \\ d_{r21} & \cdots & . & \cdots \\ d_{rj1} & \cdots & . & d_{rji} \end{pmatrix} \tag{12}$$

where d_{r12} is the ratio of the distance between classes 1 and 2 using the covariance matrix for class 2. The sum of the matrix elements represents the quality of class mean separation using the specified feature subset. That subset resulting in the highest summed distance ratio

$$D_r^l = \sum_{l=0}^{i} \sum_{m=0}^{j} d_{rji} \tag{13}$$

should represent the optimal subset of features.

This metric was used in conjunction with the GML classifier. The results of the study presented in Rosenblum (1990) demonstrated that the thresholded Mahalanobis-like distance D_r produced classification accuracies equivalent to those obtained via Transformed Divergence, yet required approximately 1/6 the computational time.

4.1.4 Forward Sequential Band Selection (FSBS)

While the Bhattacharyya Distance used in the JM measurement was presented earlier in section (4.1.2) as computationally intensive without substantially greater classification accuracy as compared to Thresholded Divergence, a different approach presented in Hardie (1994) seems promising for optimal spectral band selection.

Hardie (1994) strongly suggests using prescreening to initially eliminate extraneous spectral bands. Once this is accomplished, an optimal set can be determined. Used in conjunction with target/background multispectral imagery, this technique as it is presented assumes sufficient training data from both the target and background class. The procedure is as follows:

(a) Select the band with the highest B-distance of the N candidates.

(b) Pair each of the remaining (N-1) bands with that selected in step (a) and select the band yielding the largest 2-D B-distance.

(c) Pair the remaining (N-2) bands with the pair selected in step (b); choose the band yielding the largest 3-D B-distance.

(d) Repeat the procedure until the desired number of bands, J, have been selected. The B-distance is written:

$$B_{ij}=\frac{1}{8}(\mu_i-\mu_j)^T\left(\frac{\Sigma_i+\Sigma_j}{2}\right)^{-1}(\mu_i-\mu_j)+\frac{1}{2}\ln\frac{\left|\frac{\Sigma_i+\Sigma_j}{2}\right|}{\sqrt{|\Sigma_i||\Sigma_j|}} \qquad \textbf{(14)}$$

where μ is the class mean and Σ is the class covariance matrix. Where training data are required, the class mean vectors and covariance matrices can be approximated by the training sample class mean and covariance. This process is referred to throughout the course of this study as Forward Sequential Band Selection (FSBS). Using the above procedure, the number of B-distance computations is:

$$calculations=J(N-\frac{J}{2}+\frac{1}{2}) \qquad \textbf{(15)}$$

Hardie was able to show using this method that the set of optimal spectral bands for target identification varied according to class.

4.1.5 Spectral Basis Functions

A technique introduced by Price (1994) expands the image over a set of basis functions to determine the location and width of the spectral intervals which optimize the system. The idea of using basis functions to approximate a distribution is not new. The well-known Fourier series is perhaps the best known set of basis functions. The Fourier representation may be used to approximate the square wave function as a sum of sines and cosines. The square wave function is defined:

$$f(x)=\begin{cases} 1, & 2n\pi<x<(2n-1)\pi \\ 0, & x=n\pi \\ -1, & (2n-1)\pi<x<2n\pi \end{cases} \qquad \textbf{(16)}$$

The Fourier Series can be written:

$$f(x)=a_0+\sum a_n\cos nx+\sum b_n\sin nx \qquad \textbf{(17)}$$

where a_0, a_n and b_n are coefficients and the periodic functions *cos(nx)* and *sin(nx)* are basis functions. Definite integrals relate the coefficients to the periodic functions as follows:

$$a_n=\frac{1}{\pi}\int_0^{2\pi} f(t)\cos(nt)dt \qquad \textbf{(18)}$$

$$b_n=\frac{1}{\pi}\int_0^{2\pi} f(t)\sin(nt)dt \qquad \textbf{(19)}$$

Figures (3) and (4) illustrate how individual sine curves may be summed to approximate the square wave function defined in Equation (16).

Figure 3: Individual Sine Curves

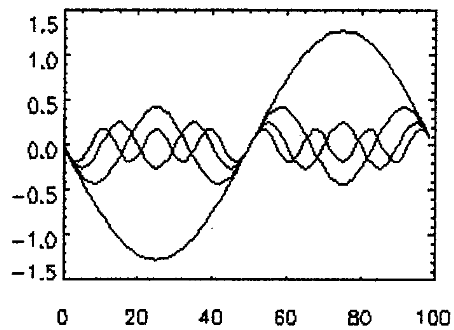
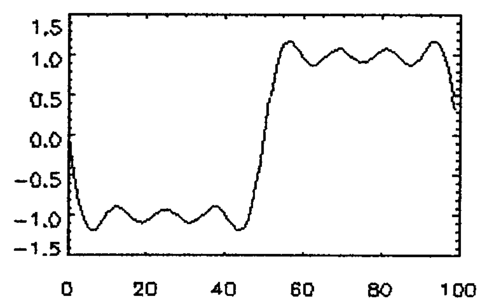


Figure 4: Summed Sine Curves - Step Function Approximation



In a similar manner, Price (1994) approximates spectra as the expansion over a set of basis functions

$$x \cong \sum_{i=1}^{M} S_i \varphi_i(\lambda) \tag{20}$$

where the N-dimensional vector $\boldsymbol{x}$ represents a measured spectrum, the coefficients S_i

are wavelength integrals, and $\varphi(\lambda)$ are the basis function spectral shapes.

4.1.5.a Development

Price (1992) bases the development of this approximation on a three-step iterative process. In the first step, he uses Gram-Schmidt orthonormalization to select a preliminary set of M-dimensional basis vectors. We can begin by defining $\boldsymbol{x}$ to be a spectral measurement of dimensionality N,

$$x^{\alpha}=(x_1,x_2,\ldots x_n) \tag{21}$$

and (δx) to be a set of residual measurement vectors of level K. For K=0, (δx) represents the difference from the mean of the data set ($\delta x = \boldsymbol{x} - \langle x \rangle$) while for values of K > 0, (δx) can be written $\delta x = \boldsymbol{x}$ - (*fit to level K*). Based on these definitions, we can construct a basis iteration K+1 by selecting vectors δx for which $|\delta x| > \varepsilon$. Selection of ε will be described shortly. The process begins by averaging the first M spectra which obey the condition $|\delta x| > \varepsilon$ to construct a unit vector

$$e_1=\frac{\frac{1}{M}\sum \delta x}{|\frac{1}{M}\sum \delta x|} \tag{22}$$

Subsequent vectors are reduced in this process by subtracting the previously obtained projections. For example, after $\mathbf{e}_1$ is obtained, each vector is reduced to

$$\delta x'=\delta x-(e_1\delta x)e_1 \tag{23}$$

Subsequent unit vectors $\mathbf{e}_i$ are based on the previously obtained vectors $\mathbf{e}_{i-j}$. An initial value for ε is determined by trial and error such that M vectors are selected. This value is then reduced accordingly in subsequent iterations. After several iterations, we can represent each spectrum by

$$\delta x = \sum (e_i \circ \delta x) e_i = \sum c_i e_i + r \tag{24}$$

where $c_i = (\mathbf{e}_i \cdot \delta x)$ and $\boldsymbol{r}$ is the residual.

In step two, Price (1992) derives the principal components of the covariance matrix $|c_i c_j|$ to calculate the M-dimensional eigenvectors $\mathbf{C}_i$ that exhibit most of the total variability in the original spectrum. These M eigenvectors may be used to approximate the N-dimensional eigenvectors

$$E_i = \sum_{j=1}^{M} C_{ij} e_j \tag{25}$$

of the N-dimensional original data. We can express δx at level K as

$$\delta x \simeq \sum_{i=1}^{M} c_i E_i \tag{26}$$

where $c_i = (\mathbf{E}_i \cdot \delta x)$. It is important to note that the original $\mathbf{e}_i$, as well as the vectors $\mathbf{E}_i$, are subject to noise in the measured spectra.

The third step is based on the understanding that most of the variability in the spectra is described by the first few eigenvectors, **E**, that these eigenvectors vary continuously and relatively slowly with respect to wavelength, and that each eigenvector represents the spectral behavior across the full spectrum. With this in mind, a single parameter can be written

$$S_i^\alpha = \int \delta x^\alpha d\lambda_i = \frac{1}{[\lambda_i(\max) - \lambda_i(\min)]} \int_{\lambda_i(\min)}^{\lambda_i(\max)} \delta x^\alpha d\lambda \tag{27}$$

where the integral across the broad-band interval from the spectral region where the first eigenvector is large describes the total spectral behavior of the eigenvector. It is important to note that the integral value is simply an approximation due to the exclusion of the smaller eigenvector contributions to the broad-band integral. The obtained integral value can then be used to construct a wavelength-dependent fitting function

$$\delta \boldsymbol{x}^\alpha \simeq \varphi_i(\lambda) S_i^\alpha \tag{28}$$

where φ is determined by the best fit across the data set

$$\varphi_i(\lambda) = \frac{<\delta \boldsymbol{x}^\alpha S_i^\alpha>}{<(S_i^\alpha)^2>} \tag{29}$$

The definition of the normalization for φ is

$$\int \varphi_i d\lambda_i = \frac{1}{[\lambda_i(\max) - \lambda_i(\min)]} \int_{\lambda_i(\min)}^{\lambda_i(\max)} \varphi_i d\lambda = 1 \tag{30}$$

and the value $\delta \mathbf{x}$ at each iteration level K is approximated by

$$\delta x_K^{\alpha} \simeq \varphi_k(\lambda) S_k^{\alpha} = \varphi_k(\lambda) \int \delta x^{\alpha} d\lambda_K \tag{31}$$

Level K is reached when the residual vectors are dominated by noise or no longer display an observable pattern. Convergence depends on accurate selection of the spectral interval corresponding to the first eigenvector, $\mathbf{E}_1$. Finally, since the mean of the data set is well described by φ, it follows that

$$x^{\alpha} \simeq \sum_{i=1}^{K} \varphi_i(\lambda) S_i^{\alpha} \tag{32}$$

which is the approximation to the measured spectrum x at level K.

4.1.5.b Application

Initial Interval Selection

Assuming no *a priori* knowledge of the data set under consideration, Price (1994) initiates interval selection for the given multispectral spectrum $\mathbf{x}$ by averaging the spectrum over a fixed number of spectral data points, where $\bar{\mathbf{x}}$ represents the averaged spectra:

$$\overline{x_1} = \sum_{j=1}^{Z} x_j \tag{33}$$

$$\overline{x_2} = \sum_{j=Z+1}^{2Z} x_j \tag{34}$$

Using these averaged values, the cosignal matrix, C_{ij}, is calculated:

$$C_{ij}=\frac{1}{Z}\sum\overline{x_i x_j} \tag{35}$$

where the trace of the cosignal matrix represents an estimate of the total variance in the data. A trial spectral interval $\overline{\mathbf{x}}_h$ is selected. The remaining spectral measurements, $\overline{\mathbf{x}}_i$, are then transformed due to a reduction by their correlation with the value for the interval *h* such that:

$$\overline{x_i^{\prime}}=\overline{x_i}-\frac{r_{ih}-\sigma_i}{\sigma_H \overline{x_h}} \tag{36}$$

where

$$r_{ih}=\frac{\langle\overline{x_i s_h}\rangle}{(\sigma_i\sigma_h)} \tag{37}$$

and

$$\sigma_i^2=\langle\sum\overline{x_i^2}\rangle \tag{38}$$

It then becomes clear that the revised cosignal matrix can be written:

$$C_{ij}^{/}=C_{ij}-\frac{C_{ih}C_{jk}}{\sigma_h^2} \tag{39}$$

where the corresponding residual trace is determined to be:

$$Tr(C_{ij})-Tr(C_{ij}^{/})=\Sigma_{i\neq h}\sigma_i^2 r_{ih}^2 \tag{40}$$

Price (1994) uses this calculation to determine an initial estimate of spectral intervals in which residual is determined for each possible value of *h*. The value of *h* resulting in the smallest residual value is selected, and the entire process is repeated beginning with the new cosignal matrix C_{ij}^{1} for selection of the remaining spectral intervals. Reduction of the residual by 99.9% is considered a reasonable result. Using the determined spectral intervals in the spectral basis function equations provides an initial approximation to the set of optimal spectral intervals.

Basis Function Calculation

The set of basis functions is calculated using the determined initial spectral intervals and the following sequence (Price, 1994). From theory, we know that each S_i is the integral over the selected interval [λ_i(min), λ_i(max)] less the previously determined fitting series:

$$S_i=\int\delta x_i d\lambda_i=\int(x-\sum_{j=1}^{i-1}S_j\varphi_j)d\lambda_i \tag{41}$$

We can define:

$$s_i = \int x d\lambda_i \tag{42}$$

and

$$b_{ij} = \int \varphi_j d\lambda_i \tag{43}$$

so that $S_1 = s_1$ and for $i > 1$

$$S_i = s_i - \sum_{j=1}^{i-1} b_{ij} S_j \tag{44}$$

which can also be written:

$$S_i = \sum_{j=1}^{i} d_{ij} s_j \tag{45}$$

where $d_{ii} = 1$. By substitution and changing the order of summation, then, we obtain:

$$S_i = s_i - \sum_{j=1}^{i-1} \sum_{k=j}^{i-1} b_{ik} \, d_{kj} \, s_j \tag{46}$$

A comparison of eq(45) and eq (46) reveals that:

$$d_{ij} = -\sum_{k=j}^{i-1} b_{ik} d_{kj} \tag{47}$$

Substituting the above expressions into the equation for the basis function φ_i , we see that

$$\varphi_i = \frac{\langle (x - \sum_{j=1}^{i-1} S_j \varphi_j)(\sum_{k=1}^{i} d_{ik} s_k) \rangle}{\langle (\sum_{j=1}^{i} d_{ij} s_j)(\sum_{k=1}^{i} d_{ik} s_k) \rangle} \tag{48}$$

If the quantity P is defined such that

$$P_{ij} = \sum_{k=1}^{i} \sum_{l=1}^{i} d_{ik} d_{jl} \langle s_k s_l \rangle \tag{49}$$

then the basis function can be written more simply:

$$\varphi_i = \frac{\left(\sum_{j=1}^{i} d_{ij} \langle \mathbf{x} s_j \rangle - \sum_{j=1}^{i-1} P_{ij} \varphi_j \right)}{P_{ii}} \tag{50}$$

The sequence of basis function calculations is as follows:

(a) Compute $<\mathbf{x}s_i>$ and $<s_i s_j>$ for i and j from 1 to M;

(b) Compute the first basis function $\varphi_1 = <\mathbf{x}s_1>/<s_1^2>$;

For i > 1,

(c) Compute b_{ij} with equation (43);

(d) Compute d_{ij} with equation (47); and

(e) Calculate φ_i in terms of b_{ij}, d_{ij}, $<s_i s_j>$ and the lower-order basis functions φ_j using equations (49) and (50).

Interval Refinement

Additional refinement of the preliminary basis functions is required, however, to produce an optimal set. Price (1994) suggests the following procedure:

(a) Broaden or narrow the preliminary spectral interval so that a central element of the spectral basis function, φ, exceeds a value of 0.85 - 0.90 . While broadening the interval increases the signal-to-noise ratio, narrowing the interval eliminates regions with poor correlation to the main signal.

(b) In the case of overlap such that both basis functions are above 0.85-0.90, a wavelength should be selected which separates the two intervals at the value at which the preliminary basis functions are equal.

(c) Using the finalized spectral intervals, calculate the set of optimal basis functions using equations (41)-(50).

Price used this technique in conjunction with reflectance data sets of special interest to agriculture covering the range 0.40 - 2.50 μm. It was found that, for the data considered, 15-25 spectral intervals were sufficiently representative of the range of spectral variability. However, the presence of minerals and artificial materials required more spectral intervals for adequate representation.

4.1.6 Summary

The three-band selection algorithms chosen for further analysis are Thresholded Divergence (TD), Spectral Basis Functions (SBF) and Forward Sequential Band Selection (FSBS). Thresholded Divergence was selected for its demonstrated effectiveness when used in conjunction with GML classification. The FSBS technique uses Bayesian statistics similar to those used in TD, but specifically for the task of target identification rather than land cover classification. Finally, SBF was selected for its mathematical robustness and lack of specific classification algorithm for which it was intended. Each of the three band-selection techniques will be applied to the known or predicted class statistics of the sample images to select the *k* best bands. The selected optimal band sets selected by the three techniques will be compared. The images will then be classified using Gaussian Maximum Likelihood for landcover classification, and Signal-to-Clutter Ratio and Log-Likelihood Test Ratio for target identification. The landcover classification results will be entered into confusion matrices based on both independent sampling and stratified random sampling for analysis and comparison. Similarly, the target-identification results will be entered into ROC curves based on both independent sampling and stratified random sampling for analysis and comparison. In this way,direct comparisons can be made of the results of each band selector for a single image and across the range of images with respect to both landcover classification and target identification.

4.2 Classification Techniques

Numerous techniques exist for the classification of multispectral images. Differences between the various methodologies arise in the implied assumptions, statistical rigor, and desired output. As this study will concentrate on two of the more predominant classification types, landcover and target/background, the methods selected for discussion are accepted and established classification techniques.

4.2.1 Gaussian Maximum Likelihood

Frequently, a multispectral image is segmented into various distinct classes according to material or landcover type. While a number of techniques perform this type of classification, this study will focus on Gaussian Maximum Likelihood classification under Bayesian assumptions. Previous studies (Nessmiller, 1995) have shown GML to be a solid approach with classification accuracies better than those acquired using Fuzzy K-Means techniques and approaching those of ARTMAP. A detailed presentation of GML classification is found in Schott (1997).

We define a column vector (**X**) comprised of digital count values (DC) in each of J spectral bands for each pixel, where

$$\boldsymbol{X}^{\boldsymbol{T}}=[DC_1, DC_2, ..., DC_j] \quad \textbf{(51)}$$

The multivariate mean for class i can be written

$$\boldsymbol{M}^{\boldsymbol{T}}=[DC_{iavg1}, DC_{iavg2}, ..., DC_{iavgj}] \quad \textbf{(52)}$$

where the K classes are represented by $i = 1, \ldots, K$.

Bayesian probability theory defines the *a posteriori* probability that a pixel with spectral vector **X** belongs in class i as $p(i|\mathbf{X})$:

$$p(i|\boldsymbol{X}) = \frac{p(\boldsymbol{X}|i)p(i)}{p(\boldsymbol{X})} \tag{53}$$

where the *a priori* probability, $p(i)$, is the probability of a randomly sampled pixel being in a given class; the conditional probability, $p(\mathbf{X}|i)$, describes the probability of a vector occurring subject to the condition that we are sampling from the ith class; and $p(\mathbf{X})$ is the probability of the digital count occurring anywhere in the image.

When the class histograms can be assumed to be approximately Gaussian, the mean vector and covariance matrix of the training data can be used to estimate the conditional probability according to :

$$p(\boldsymbol{X}|i) = \frac{1}{(2\pi)^{j/2}|\boldsymbol{S}_i|^{1/2}} e^{[-\frac{1}{2}(\boldsymbol{X}-\boldsymbol{M}_i)^T \boldsymbol{S}_i^{-1}(\boldsymbol{X}-\boldsymbol{M}_i)]} \tag{54}$$

where $\mathbf{S}_i$ is the covariance matrix for class i:

$$\boldsymbol{S}_i = \begin{bmatrix} \sigma_{i11} & \sigma_{i12} & \cdots & \sigma_{i1j} \\ \sigma_{i21} & \cdots & . & \cdots\cdots \\ \sigma_{ij1} & \cdots & . & \sigma_{ijj} \end{bmatrix} \tag{55}$$

The covariance σ_{jk} between spectral bands *j* and *k* for class *i* is written:

$$\sigma_{ijk}=\sum_{q=1}^{N}\frac{(DC_{ij}(q)-DC_{ijavg})(DC_{ik}(q)-DC_{ikavg})}{N-1} \tag{56}$$

for N pixels in the sample set.

Substituting back into equation (53) yields the *a posteriori* probability for **X** if the data are normally distributed.

$$p(i|\boldsymbol{X})=\frac{p(i)}{p(\boldsymbol{X})(2\pi)^{j/2}|\boldsymbol{S}_i|^{1/2}}e^{[-\frac{1}{2}(\boldsymbol{X}-\boldsymbol{M}_i)^T\boldsymbol{S}_i^{-1}(\boldsymbol{X}-\boldsymbol{M}_i)]} \tag{57}$$

However, since p(**X**) is the same for all classes and thus will not alter the rank ordering of the *a posteriori* probabilities, it can be eliminated from the classifier to obtain a simpler expression:

$$D_i'=p(\boldsymbol{X}|i)p(i) \tag{58}$$

Additional simplification is achieved by redefining D′ via a logarithm:

$$D_i=\ln[p(i)]-\frac{j}{2}\ln(2\pi)-\frac{1}{2}\ln|\boldsymbol{S}_i|-\frac{1}{2}(\boldsymbol{X}-\boldsymbol{M}_i)^T\boldsymbol{S}_i^{-1}(\boldsymbol{X}-\boldsymbol{M}_i) \tag{59}$$

Values of the mean vector $\mathbf{M}_i$ and the covariance matrix $\mathbf{S}_i$ can be estimated from training data, and the *a priori* probability p(*i*) can be estimated. The pixel corresponding to the spectral vector **X** is assigned to the class yielding the highest value for D_i. Where the class probabilities can be assumed equal and the sign of the function is reversed, the discriminant can be written:

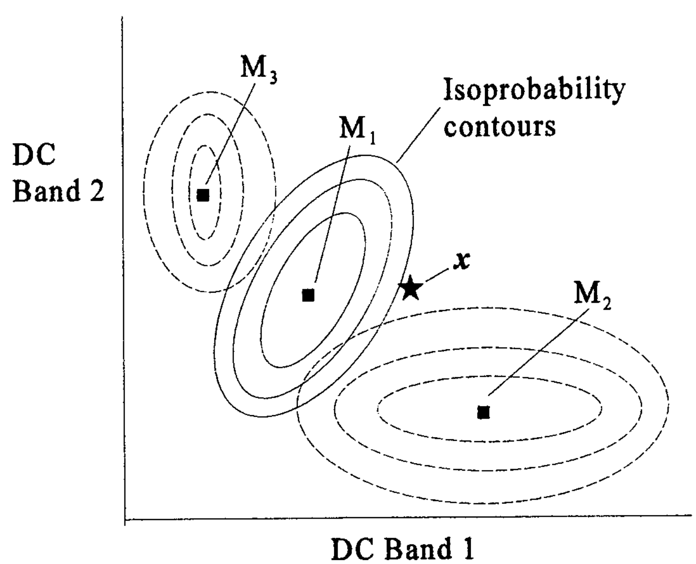
$$D_i = \ln|S_i| + (X - M_i)^T S_i^{-1} (X - M_i) \qquad \textbf{(60)}$$

Finally, in the case where both the class probabilities p(i) and the class covariances S_i are equal, the first three terms of D_i no longer contribute to the discriminating ability of the metric. The discriminant then reduces to

$$D_i = (X - M_i)^T S^{-1} (X - M_i) \qquad \textbf{(61)}$$

which is commonly referred to as the square of the Mahalanobis distance. Figure (5) provides a visualization of GML classification of a two-band image with three classes.

Figure 5: GML Classification of a Two-Band Image (Allen, 1997)



Each ellipsoid is representative of the GML discriminant value and centered about its multivariate mean **M**. In this case, the pixel vector $\boldsymbol{x}$ would be classified as a member of class 1. Diagonal ellipsoids are the result of correlation between class digital counts in the two spectral bands.

When using the GML classifier, it is crucial that the training data set be sufficiently robust, the data approximate a Gaussian distribution, and that all classes are included in the training data.

4.2.2 Signal to Clutter Ratio

A second desirable use for multispectral imagery is the detection of small targets in highly structured backgrounds. In signal detection, noise is loosely defined to be any process that can obscure or eliminate the pattern to be detected, and the signal-to-noise ratio (SNR) is used to evaluate the effect of system noise on the output. In multispectral imagery used for target detection, the background pixels act as noise. However, since this noise is not internal to the system, it is commonly referred to as clutter, and the signal-to-clutter ratio (SCR) is used as a measure of target detectability. (Thomas, 1994)

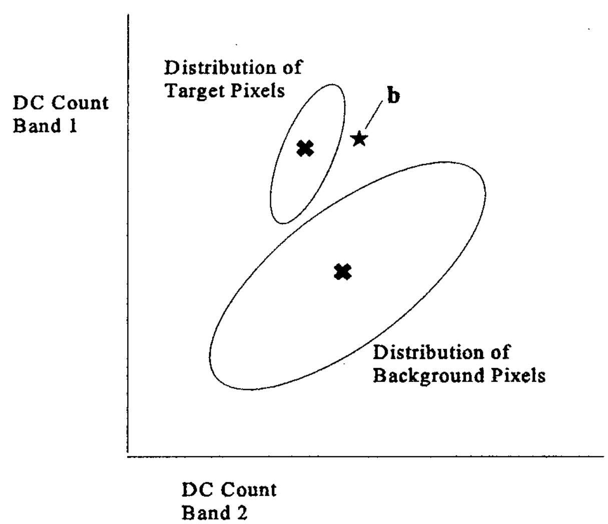
Mathematically, the multidimensional SCR can be expressed in terms of the spectral signature of the target, **b**, and the covariance matrix of the background clutter, **M** (Kanodia *et* al, 1996; Stocker *et al.*, 1990):

$$SCR=[\boldsymbol{b}^{T}\boldsymbol{M}^{-1}\boldsymbol{b}]^{1/2} \qquad \textbf{(62)}$$

It is interesting to note that the SCR is similar to the square root of the aforementioned Mahalanobis distance, although the target class mean vector is not subtracted from the spectral signature of the target. Hardie (1994) additionally points out that the SCR measure is essentially the first term of the Bhattacharyya distance represented in Equation (14) in the case where $\mu_j = 0$, although the SCR does not account for class separability based on covariance differences.

In the course of classification, the SCR acts as a hypothesis test. As described by Thomas (1994), the vector **b** represents an image pixel such that the relative position of **b** with respect to the clutter center is used to assign the pixel to the target or background class. The elliptical decision boundary for this two band space is determined using the sample mean and covariance estimates. A graphical representation of SCR classification is shown in Figure (6). In this hypothetical case, **b** would more likely be assigned to the target class.

Figure 6: SCR Graphical Representation (Thomas, 1994)



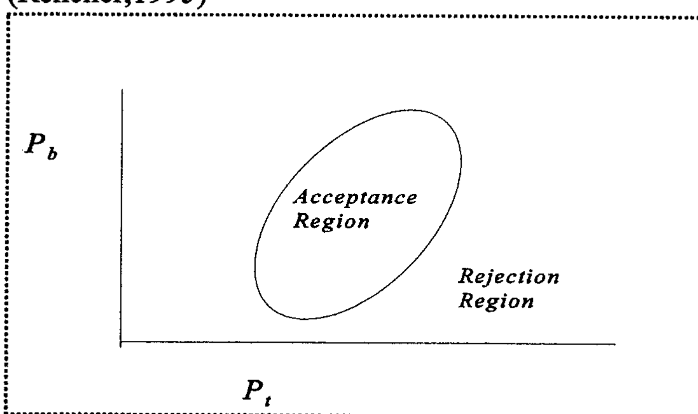
4.2.3 Log-Likelihood Test Ratio

A second commonly used classification technique for target detection is the Log-Likelihood Ratio test described in Yu, *et al.*(1993), Stocker, *et al.*(1990), and Hardie (1994). An optimum detector is defined as that which maximizes the probability of detecting a signal pattern, or similarly, that which minimizes the probability of classification error. Assuming two classes (target and background), hypotheses can be defined in which the symbol $>^{Hb}$ indicates that the spectral vector **x** belongs to the background class while the symbol $>^{Ht}$ indicates that **x** belongs to the target class. Bayesian statistics define a likelihood ratio in which :

$$l(x) = \frac{p(x|H_t)}{p(x|H_b)} >^{H^t} \frac{P_b}{P_t} \tag{63}$$

where $p(\mathbf{x}|H_b)$ and $p(\mathbf{x}|H_t)$ are the conditional probability density functions for the observed spectral vector **x**. P_b and P_t are the *a priori* probabilities. Using the likelihood

Figure 7: Elliptical Acceptance Region (Rencher,1995)



function, if $l(\mathbf{x}) > P_b/P_t$ the pixel is classified as target; if not, it is classified as background. A graphical representation of this classification process is provided in Figure (7).

It can be useful (Hardie, 1994) to apply the logarithm to the likelihood function to obtain:

$$-\ln(l(x)) = -\ln(p(x|H_b)) + \ln(p(x|H_t)) <^{H_t} \ln(\frac{P_t}{P_b}) \quad \textbf{(64)}$$

In the case where both the target and background classes are assumed to be Gaussian distributions, the decision rule can be written as a quadratic function in $\mathbf{x}$:

$$h(x) = \frac{1}{2}(x-\mu_b)^T\Sigma_b^{-1}(x-\mu_b) - \frac{1}{2}(x-\mu_t)\Sigma_t^{-1}(x-\mu_t) >^{H_t} \ln\frac{P_t}{P_b} - \frac{1}{2}\ln\frac{|\Sigma_b|}{|\Sigma_t|} \quad \textbf{(65)}$$

where μ represents the class mean and Σ is the class covariance matrix.

In the special case where the class covariances are equal, the decision rule reduces to a linear function in $\mathbf{x}$; if $\mu_b = 0$ the decision rule essentially reduces to the Signal-to-Clutter Ratio. Unlike SCR, the Log-Likelihood Ratio test considers class covariances in the classification process.

4.3 Classification Accuracy

Clearly, the optimal means for assessing classification accuracy would be to compare the classified image with ground-truth data for each point in the image. Such an intensive comparison would be impractical and unreasonable; if the entire ground truth were known there would be no reason to perform the classification. Instead, sampling methods are used to assess accuracy.

4.3.1 Sample Selection

Richards (1993), Schott (1997), and Rosenblum (1990) discuss the importance of sample selection for successful evaluation. Dependent/independent analysis is considered a simple, yet less accurate approach. Since the initial training of the classifier involves selection of class-representative pixels, it is possible to use only a percentage of the selected pixels to develop class statistics; the remainder may be used to assess accuracy. Those pixels used by the classifier are considered dependent while the remainder are considered independent as they do not influence classification. Weaknesses affiliated with this method include a lack of robustness due to the limited nature of the sample set.

A second option calls for random sampling of individual pixels from across the image for comparison with reference data. In this way, inaccuracies due to correlation are eliminated. A potential problem in a purely random approach exists in the correlation between the number of pixels sampled from a given class and the relative size of that class in the image; a large class will have a larger sample size than a smaller class. An approach suggested by Richards (1993) calls for stratified random sampling in which the image is divided into user-defined strata based on thematic class. Each stratum then is randomly sampled to determine classification accuracy. This method, used in Rosenblum (1990), yielded lower, more conservative classification accuracies which were estimated to more closely resemble actual results on the whole image.

4.3.2 Confusion Matrices

The results of such accuracy assessment can be expressed in a tabular form referred to as a confusion matrix and discussed in Schott (1997) and Richards (1993). A sample confusion matrix is shown in Table (1) where the percentages represent the proportion of pixels correctly and incorrectly labeled by the classifier. In many cases the percentages of correct classifications are averaged to provide an overall classification

Table 1: Sample Confusion Matrix

Sample Confusion Matrix							
	% classified as class						
	Class	1	2	3	4	5	
Actual Class	1	93.5	0.0	2.2	0.0	4.3	
	2	0.0	29.7	65.7	0.8	3.8	
	3	12.3	0.0	87.4	0.3	0.0	
	4	0.0	0.0	1.4	98.6	0.0	
	5	0.0	0.0	0.0	0.0	100	
	% Accuracy						**81.8**

accuracy. This method of accuracy assessment will be used in conjunction with the GML classification results.

4.3.3 Receiver Operating Characteristic Curves

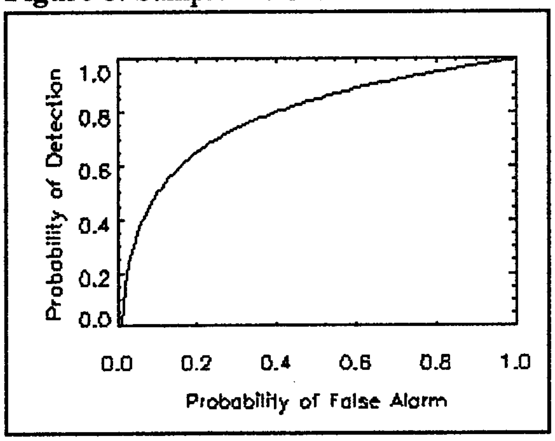
In the case of signal detection, isosensitivity curves, also known as receiver operating characteristic (ROC) curves, are commonly used to assess accuracy (Snodgrass, 1975). When a signal is present in background clutter, the algorithm or individual tasked with signal detection can produce any of four possible results. A true positive("hit") is defined as the correct identification of the signal; a false positive "false alarm") corresponds to any pixel incorrectly identified as signal when it really belongs to clutter; a false negative ("miss") describes any signal pixel not identified as signal; and finally a true negative ("correct rejection") corresponds to any pixel correctly identified as clutter. When a sample set is tested with respect to this criteria, probabilities for each of the four categories can be calculated. These probabilities are frequently illustrated in matrix or plot format. In matrix form, the probabilities are displayed as illustrated in Table (2) where *S* and *N* refer to signal and clutter, respectively. Using this notation, *Pr(S/N)* signifies the probability of categorizing a pixel as signal given that it belongs to the clutter class.

Table 2: Stimuli/Response Metric

Response		
Stimuli	Hit: *Pr(S/S)*	Miss: *Pr(N/S)*
	False Alarm: *Pr(S/N)*	Correct Rejection: *Pr(N/N)*

These probabilities can also be presented as isoprobability, or receiver operating characteristic (ROC), curves in which the probability of a hit is plotted against the probability of a false alarm. A sample ROC curve is shown in Figure (8). This technique will be used in conjunction with the Signal-to-Clutter Ratio and Log-Likelihood Ratio classification results.

Figure 8: Sample ROC Curve



5.0 APPROACH

While it is unlikely that a single algorithm, or even a series of algorithms, can provide results comparable to those obtained with the case-specific techniques, it is conceivable that such a process might provide sub-optimal, yet reasonable, results across the range of scenarios and exploitation algorithms. With this in mind, this study will focus on the implementation of Thresholded Divergence, Spectral Basis Functions, and Forward Sequential optimal spectral band selection techniques across multiple scenarios and multiple classification algorithms. The effectiveness of each of these band selection techniques will be evaluated with respect to classification accuracy metrics to determine if any one band selection algorithm proves effective across the range of scenarios, classification algorithms, and input parameter sets.

5.1 Image Data

Images selected for this series of tests encompass the necessary characteristics for both landcover classification and target identification. Landcover classification requires a wide sampling of terrain and content, whereas target identification requires that a clear target be distinguished from background clutter. In this particular study, images containing landcover classes and target/background pairs with similar spectral characteristic were particularly desirable for stressing the band selection algorithms. Two M7 images and two Hydice images represented a sufficiently robust data set incorporating all of the required characteristics.

5.1.1 Tank Scene

The image referred to throughout this study as the *tank* scene (Figure 9) was captured as part of the Southern Rainbow collection by the Environmental Research Institute of Michigan (ERIM) using a 16-band M7 aerial line scanner. The bandpasses used in this study are listed in Table (3); the thermal band (16) was not used in the study. This scene presented a range of natural and man-made land cover classes including parking lots, building roofs, roads, forest, and scrub. The generic scrub class was sub-divided into multiple classes in order to stress the band selection algorithms. Man-made building roofs served as targets for the target identification algorithms.

Figure 9: Tank Scene

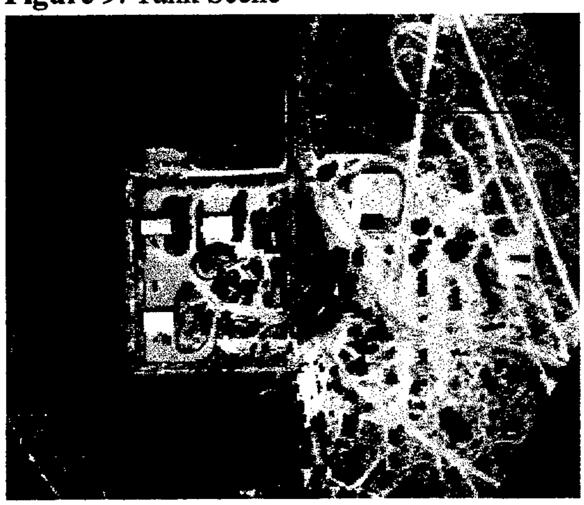


Table 3: Southern Rainbow Bandpass

M7 Band	Bandpass (μm)
1	0.45-0.47
2	0.48-0.50
3	0.51-0.55
4	0.55-0.60
5	0.60-0.64
6	0.63-0.68
7	0.68-0.75
8	0.71-0.81
9	0.81-0.92
10	1.02-1.11
11	1.21-1.30
12	1.53-1.64
13	1.54-1.75
14	2.08-2.20
15	2.08-2.37

5.1.2 Desert Scene

The scene referred to as the *desert* scene was collected using the Daedalus airborne sensor as part of the Western Rainbow Joint Camouflage Concealment and Deception (JCCD) collection. While this scene provided less variety than the *tank* scene, it included man-made vehicles (tanks) for target identification and multiple sand types with similar spectral characteristics to stress the band selection algorithms. A tent served as the target for target identification algorithms. As with the tank scene, the thermal bands were not used. The remaining 10 bandpasses are listed in Table 4.

Figure 10: Desert Scene

Table 4: Western Rainbow Bandpass

M7 Band	Bandpass (μm)
1	0.405-0.455
2	0.435-0.535
3	0.500-0.625
4	0.570-0.650
5	0.595-0.720
6	0.645-0.790
7	0.700-0.955
8	0.785-1.070
9	1.495-1.835
10	2.011-2.560

Figure 11: Desert Scene Subset

5.1.3 Panel Scene

Figure 12: Panel Scene

The scene referred to throughout this study as the *panel* scene is a portion of the ARM-HYDICE scene, Run 07, collected by the Hyperspectral Digital Imagery Collection Experiment sensor (HYDICE). The sensor is an imaging spectroradiometer with a cryogenically cooled InSb focal plane array. The bandpass of 0.40 to 2.5 microns is contiguously sampled with spectral channels of width 10 nm. This particular subset of the ARM-HYDICE site offers a range of natural and man-made landcover classes including various pasture types, water, wheat, buildings, roads and a series of man-made reflectance panels. One reflectance panel was used as the target for target/background classification.

5.1.4 Pasture Scene

Figure 13: Pasture Scene

The *pasture* scene is also a portion of the ARM-HYDICE scene, Run 07, collected by the Hyperspectral Digital Imagery Collection Experiment sensor (HYDICE). While this scene had fewer landcover classes than the *panel* scene, it included pasture, water, unknown, and various types of wheat. A small pond served as the target. Wheat fields were sub-divided to stress the band selection algorithms.

5.2 Training Data Sets

Figure 14: Sample ROI Training Set

Class training sets are collections of the digital counts in each spectral band for user-selected pixels. Landcover class training sets as well as target and background training sets were acquired from the test images using Environment for Visualizing Information (ENVI™). The data sets were applied to Eigenvector Pre-Selection, Thresholded Divergence, Forward Sequential Band Selection, Gaussian Maximum Likelihood, Signal-to-Clutter Ratio, and Log-Likelihood Test Ratio. The ROI selection tool was used to superimpose colored polygons over the image in order to designate the desired classes. A different color polygon was used for each class as shown in Figure (14). Six training class sets were built for each image: two simple landcover class sets, two sub-divided landcover class sets, and two target/background sets. Within each of the three types of ROI sets, one set was used in the band selection and classification algorithms, while the other was used for construction of the independent analysis confusion and stimuli/response matrices. The simple landcover class set differs from the sub-divided landcover class set in that some generic landcover classes were subdivided into separate classes with similar spectral characteristics in an attempt to stress the band selection algorithms.

5.3 Spectral Band Selection

Pre-selection techniques limit the initial set of candidate spectral bands, but they are generally not capable of determining the optimal set of spectral bands. For this reason, further statistical analysis is required. As discussed in section (4.1), a number of spectral band-selection techniques exist. For the most part, however, these existing studies have been fairly limited in scope in that each technique is geared towards a specific image type or classification algorithm. In many cases, the specific class statistics or post-processing algorithm are not known *a priori*. The aforementioned case-specific algorithms, then, are of limited value in the predetermination of optimal spectral bands, and an algorithm or series of algorithms effective over a range of scenarios or classification techniques would be of tremendous value.

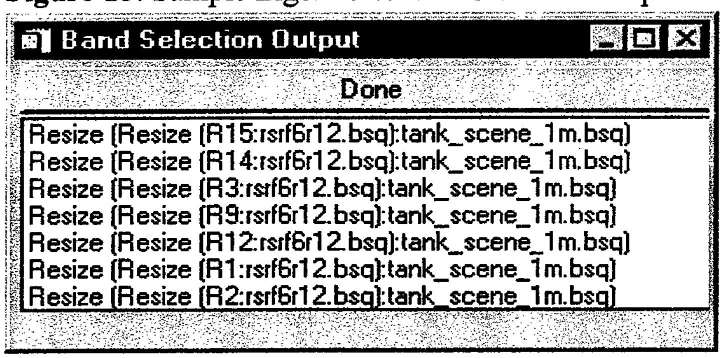
The three band-selection algorithms chosen for further analysis are Thresholded Divergence (TD), Spectral Basis Functions (SBF) and Forward Sequential Band Selection (FSBS). Thresholded Divergence was selected for its demonstrated effectiveness when used in conjunction with GML classification. The FSBS technique uses Bayesian statistics similar to those used in TD, but specifically for the task of target identification rather than landcover classification. Finally, SBF was selected for its mathematical robustness and lack of specific classification algorithm for which it was intended. Each of the three band-selection techniques was applied to the known or predicted class statistics of the sample images to select the k best bands. The optimal band sets selected by the three techniques were compared. The images were then classified using GML for landcover classification, and SCR and Log-Likelihood Test Ratio for target identification. The landcover classification results were used to construct confusion matrices based on both independent sampling and stratified random sampling for analysis and comparison. Similarly, ROC curves were computed from target-identification results based on both independent sampling and stratified random sampling for analysis and comparison. In this way, a direct comparison was made between the results of each band selector for a single image and across the range of images with respect to both landcover classification and target identification.

5.3.1 Eigenvector Pre-Selection Approach

While several techniques for spectral band pre-selection have been used, Rosenblum (1990) demonstrated that the eigenvector criteria presented in Mausel, *et al.* (1990) produced the best results. Using Principal Components Analysis, a data set of M spectral bands and N pixels is transformed into a set of M orthogonal eigenvectors, where each eigenvector is a combination of the original M spectral bands. These eigenvectors are ranked according to decreasing total variance. Thus, the first eigenvectors contain more 'information' than then later eigenvectors. Rosenblum (1990) suggests that the first K eigenvectors (those with the greatest variance) should be examined for pre-selection of the best K spectral bands. The band with the largest positive or negative loading is then chosen from each eigenvector. Selecting one band from each eigenvector assures minimal correlation in the selected set of spectral bands.

This eigenvector approach to pre-selection has been integrated into the ENVI™ environment for direct use with the input images and class training sets. Eigenvector Pre-Selection was intended to designate an adequate subset of spectral bands from which an optimal set could be chosen using band-selection algorithms rather than optimize the set of spectral bands itself. In the course of data collection, however, the eigenvector pre-selection algorithm was additionally evaluated based on final subset selection for each image. The user was required to provide the appropriate image ROI's and the desired spectral band subset size; ENVI™ outputs the selected spectral band names in widget format as illustrated in Figure (15).

Figure 15: Sample Eigenvector Pre-Selection Output



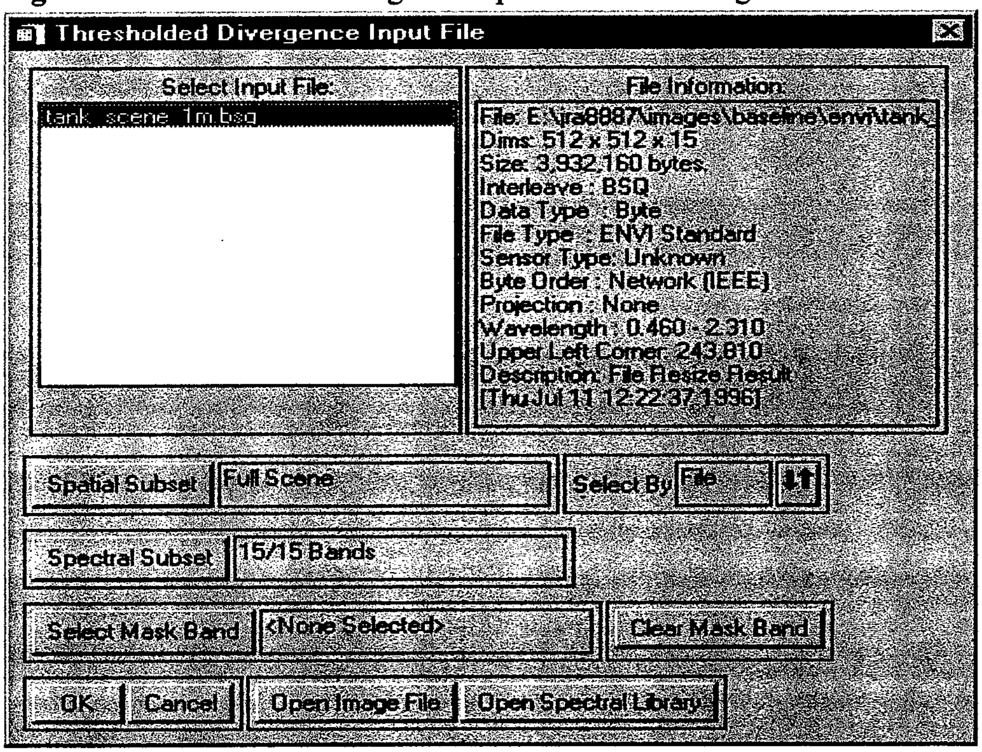
5.3.2 Thresholded Divergence

The Thresholded Divergence (TD) method of band selection discussed in Section (4.1.3) requires predetermination of the threshold value d_{thresh} used to separate features. Rosenblum (1990) arbitrarily selected a value of 1.0×10^{-15} for $P(\mathbf{X}|i)$, the probability of misclassification, so that the calculated threshold distance would be greater than the calculated distance between class means in most cases. If the threshold distance was not greater than the calculated distance between the class means, multiple subsets would produce the same maximum value and the algorithm would be unable to distinguish between subsets. Rosenblum (1990) is careful to point out that the selected value for $P(\mathbf{X}|i)$ was not meaningful since the assumption of normally distributed variables was violated. This study designated the TD process using $P(\mathbf{X}|i)=1.0 \times 10^{-15}$ as *TD original.*

A variation on the TD procedure introduced by Rosenblum (1990) was also investigated in the course of this study. This variation referred to as *TD Modified* specifically addressed those cases in which the actual distance between the class means was greater than the threshold distance, resulting in values for d_{ratio} greater than 1.0. In Rosenblum (1990), d_{ratio} values greater than 1.0 were set equal to 1.0. In *TD Modified*, the stipulation that d_{ratio} values greater than 1.0 be set equal to 1.0 was eliminated.

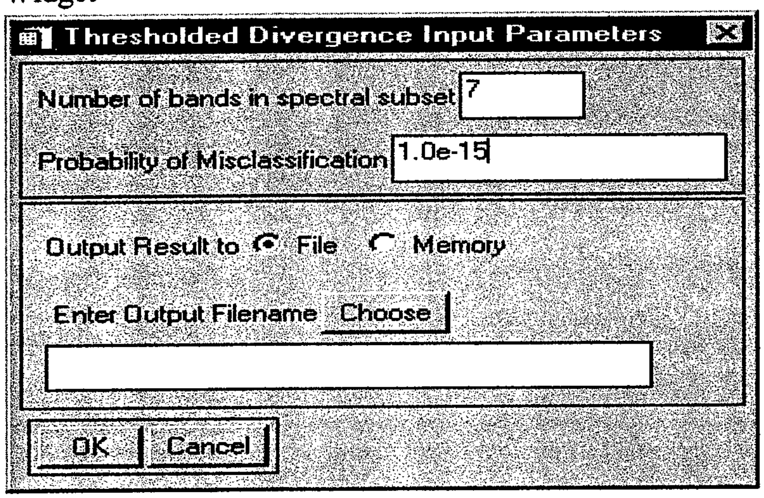
Both of the TD variations were integrated into the ENVI™ environment. In each case, the user was required to provide the image with appropriate ROI's, the desired spectral band subset size, and the probability of misclassification, $P(\mathbf{X}|i)$. The first input parameter widget shown in Figure (16) allowed the user to select the appropriate image and specify the TD input spectral band subset resulting from the Eigenvector Pre-

Figure 16: Thresholded Divergence Input Parameter Widget



Selection algorithm output. The second input parameter widget shown in Figure (17) allowed the user to input the remaining parameters as well as the desired output filename. The TD algorithm output the subset band names in a widget similar to that shown in Figure (15). For TD Threshold, a separate threshold determination routine was run prior to the TD routine. This routine simply required the input image with appropriate ROI's. Calculated values for the probability of misclassification, $P(\mathbf{X}|i)$, and threshold were printed in the IDL™ command window.

Figure 17: Thresholded Divergence Input Parameter Widget



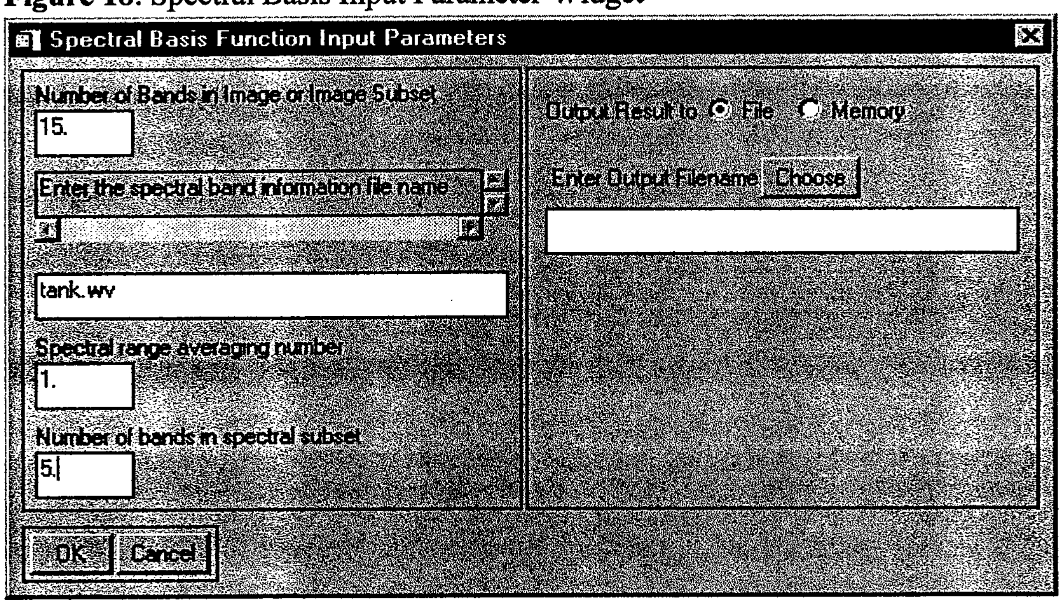
5.3.3 Forward Sequential Band Selection

The Forward Sequential Band Selection technique was integrated into the ENVI™ environment. The routine simply required an input image with appropriate ROI's and the desired spectral band subset size. Input parameter widgets were similar to those used in the TD routine discussed in Section (5.3.2). The output subset spectral band names were presented in a widget similar to that illustrated in Figure (15).

5.3.4 Spectral Basis Functions

The Spectral Basis Function technique as presented in Section (4.1.5) was integrated into the ENVI™ environment and applied to each of the four sample images. The routine required an input image (no ROI's were required in this method), the original number of bands in the input image or input image subset, the spectral band information file name, the spectral range averaging number, and the desired spectral band subset size as is shown in Figure (18). The spectral band information file for each image was built within IDL™. It consists of a 2-dimensional array whose members are the minimum and maximum wavelength values for each input image spectral band. The information file is a variation on the .wav files which accompany Hydice imagery. The spectral averaging number is the fixed number over which the input spectrum is averaged in the course of initial interval selection discussed in Section (4.1.5). The routine output initial interval selection results in the IDL™ window. Basis function results for each iteration were

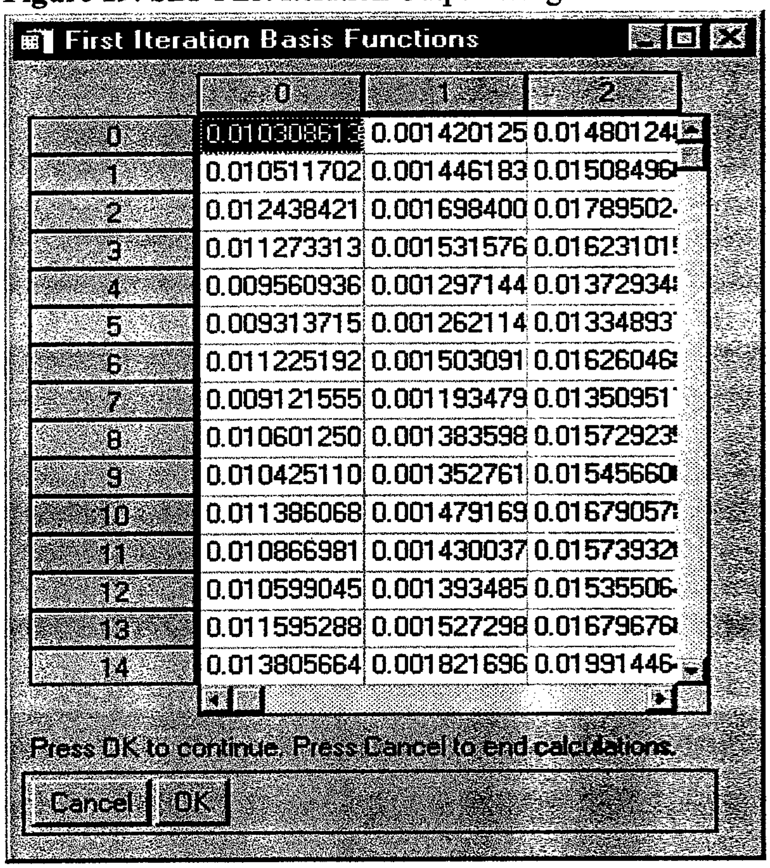
Figure 18: Spectral Basis Input Parameter Widget



output in widget format as shown in Figure (19) where the user was able to click OK to continue with another iteration, or click CANCEL to end the routine and output final subset selection results to a widget.

Initial runs on all of the sample images revealed results inconsistent with those suggested by theory presented in Price (1997). Both the *tank* and *desert* scenes produced basis function values orders of magnitude less than one. Subsequent iterations did not significantly improve the results. Both of the Hydice images produced basis function values greater than one. As a result, the decision was made to focus more specifically on

Figure 19: SBF First Iteration Output Widget



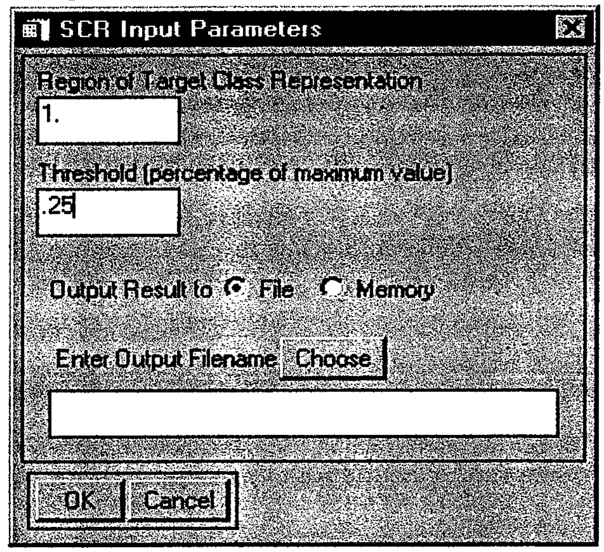
	0	1	2
0	0.01030861	0.001420125	0.01480124
1	0.010511702	0.001446183	0.01508496
2	0.012438421	0.001698400	0.01789502
3	0.011273313	0.001531576	0.01623101
4	0.009560936	0.001297144	0.01372934
5	0.009313715	0.001262114	0.01334893
6	0.011225192	0.001503091	0.01626046
7	0.009121555	0.001193479	0.01350951
8	0.010601250	0.001383598	0.01572923
9	0.010425110	0.001352761	0.01545660
10	0.011386068	0.001479169	0.01679057
11	0.010866981	0.001430037	0.01573932
12	0.010599045	0.001393485	0.01535506
13	0.011595288	0.001527298	0.01679676
14	0.013805664	0.001821696	0.01991446

the method used for initial interval selection. If the initial interval selection was shown to produce classification results comparable to those obtained by the other band selection techniques under evaluation, then the SBF method would warrant a more thorough examination. Since the initial interval selection results were not comparable to those obtained by the other band selection techniques, however, it was concluded that the SBF technique would not serve as a strong candidate for optimal band selection. As a result, a modified routine designed to perform only initial interval selection was integrated into the ENVI™ environment. This routine required the same input parameters, although the spectral range averaging number was set equal to 1.0 for all data runs in order to maintain the original bandwidths for direct comparison with output subsets from the other band selection routines. Due to array size limitations and memory allocation difficulties, full Hydice images could not be used. Instead, only image band subsets based on the Eigenvector Pre-Selection results were input into the initial interval selection routine. The *tank* and *desert* scenes were evaluated using both full and subset image spectral band sets. Selected subset band names were output to a widget similar to that shown in Figure (15).

5.4 Classification and Accuracy Assessment Algorithms

Image classification using Gaussian Maximum Likelihood, Signal-to-Clutter ratio, and Log-Likelihood test ratio in the ENVI™ environment was a straightforward process. GML, the only routine used in the course of this study provided by ENVI™, required the user to input the image with landcover ROI's and select the spectral bands in the subset under evaluation. The GML routine output a class map image ready for input into both the independent analysis and stratified random sampling confusion matrix generation routines.

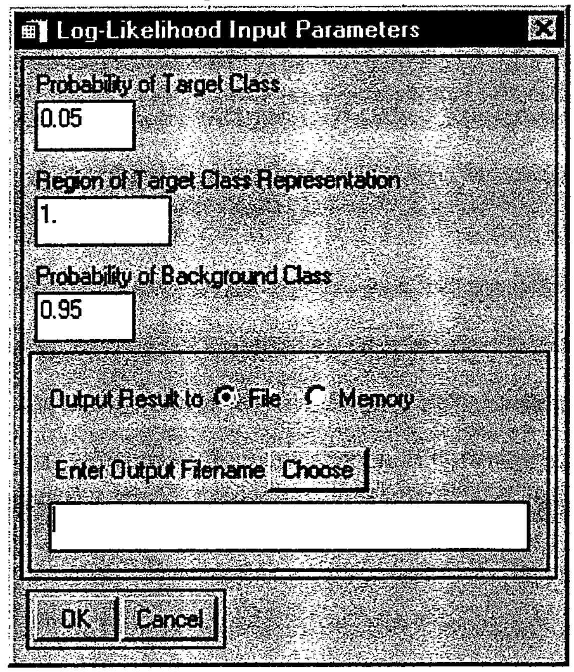
Figure 20: Signal-to-Clutter Input Parameter Widget



The SCR algorithm input parameter widget is shown in Figure (20). The user was required to provide the input image with the target/background ROI set and once again select the spectral bands in the subset under evaluation. Additional parameters required for SCR classification included the region of target class representation and the threshold value. The region of target class representation depended on how the ROI's were constructed. The default value was set to 1, in which case ROI #1 represented the target class while ROI #2 defined the background clutter. The threshold value was that value against which the calculated SCR value was compared. Pixels with SCR values greater than the threshold were classified as target pixels, while those resulting in values lower than the threshold were classified as background pixels. The user was required to input the threshold as some percentage of the maximum image pixel value. For example, a desired threshold of 25 percent of the maximum image pixel value would be entered as simply 0.25. Each spectral band subset for each image in the sample set passed through the SCR routine a minimum of three times, varying the threshold value in order to acquire sufficient data to perform ROC analysis. The SCR routine output a class map image ready for input into both the independent analysis and stratified random sampling ROC curve generation routines.

The input parameters for LOG differ only slightly from those required by SCR. The user was required to provide the input image with the target/background ROI set and once again select the spectral bands in the subset under evaluation. Additional parameters shown in Figure (21) included the region of target class representation as discussed above, the probability of the target class, and the probability of the background class. The probability of the target class is the probability that a randomly selected pixel would be a member of the target class; the probability of the background class is most simply described as (1-probability of target class). Each spectral band subset for each image in the sample set passed through the LOG routine a minimum of three times, varying the probability of target and probability of background values in order to acquire sufficient data to perform ROC analysis. The LOG routine output a class map image ready for input into both the independent analysis and stratified random sampling ROC curve generation routines.

Figure 21: Log-Likelihood Test Ratio Input Parameter Widget



Both the confusion matrix and ROC curve independent analysis accuracy assessment routines required the user to input a truth image and a class map image. The truth image was the original image accompanied by a ROI set other than that used for classification, but made up of the same landcover or target/background classes. The confusion matrix generation routine output a simple accuracy confusion matrix to both the IDL™

command window and the user-selected filename. The ROC generation routine output a stimuli/response metric in the format shown in Table (2) to both the IDL™ command window and the user-selected filename.

The stratified random sampling accuracy assessment routines were more complex. Both required the user to input an original image, a class map image, and the desired number of training points. The ROC routine additionally required the user to input the region of target class representation. The routine would randomly generate a coordinate set and check the selected pixel's class value in the class map image to make sure that the appropriate number of pixels were selected from each class. A user interface widget displayed the selected pixel coordinates and allowed the user to input the pixel's true class as shown in Figure (22). The user could independently pinpoint the appropriate pixel by simultaneously accessing the Interactive Display -> Pixel Locator option under the Functions menu in the image display window shown in Figure (23). This process was repeated until the appropriate number of pixels were queried in each class. The confusion matrix generation routine output a simple accuracy confusion matrix to both the IDL™ command window and the user-selected filename. The ROC generation routine output a stimuli/response metric in the format shown in Table (2) to both the IDL™ command window and the user-selected filename.

Figure 22: Stratified Random Sampling Class Input Widget

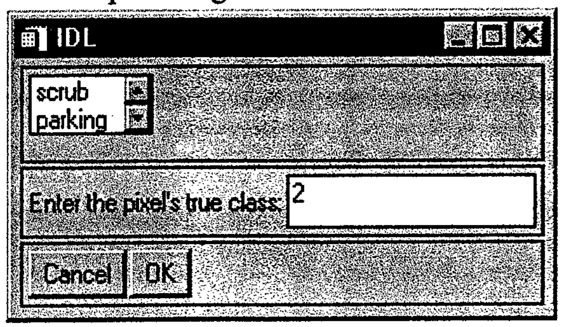
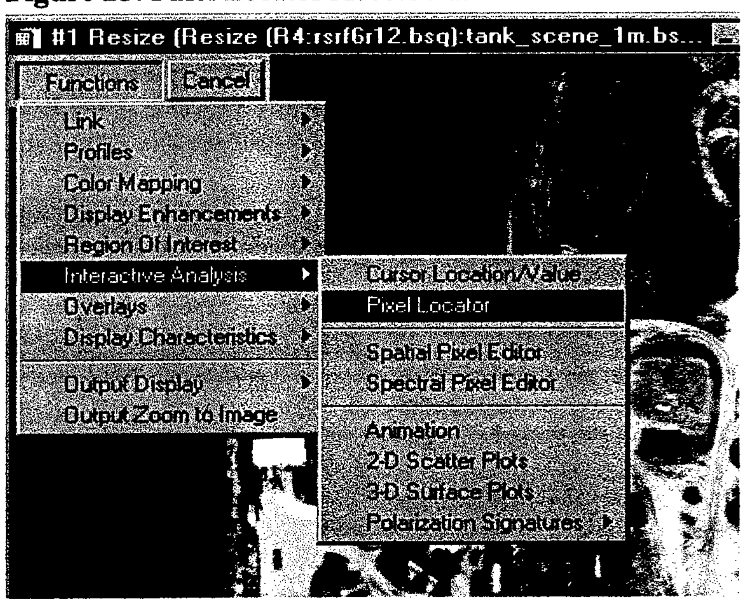


Figure 23: Pixel Locator Access Path



6.0 Results

The test metric data shown in Table (5) was collected for each image in the sample set. Two sets of Eigenvector Pre-Selection data were acquired: the first set was an initial down-select for use in subsequent band-selection while the second set was a down-select to the final image subset for direct comparison with the other band-selection techniques. The nomenclature is as follows: the first element describes the band selection technique, the second element describes the initial down-select band set used by the band selection algorithm under evaluation, and the final element describes the ROI set used. Class1 describes the generic landcover class ROI. Class2 describes the landcover class ROI in which generic landcover classes were sub-divided. Tg refers to the target/background ROI set. For example, TD orig/p1/class1 describes the subset acquired using the TD original routine, the pre-selection spectral band output using class1, and the class1 ROI's.

Table 5: Test metric for data collection.

Image Name		
Pre-select (p1)/class1	Pre-select (p2)/class2	
TD orig/p1/class1	TD mod/p1/class1	FSBS/p1/class1
TD orig/p2/class2	TD mod/p2/class2	FSBS/p2/class2
TD orig/p1/class2	TD mod/p1/class2	FSBS/p1/class2
TD orig/p1/tg	TD mod/p1/tg	FSBS/p1/tg
TD orig/p2/tg	TD orig/p2/tg	FSBS/p2/tg
SBF/p1	SBF/p2	SBF/full
Pre-select/class1	Pre-select/class2	Pre-select/tg

Complete data sets for spectral band subsets of 2 bands and 4 bands were built for each image. Each spectral band subset for each complete data set was classified and analyzed using GML, SCR, and LOG in conjunction with the appropriate accuracy assessment metric.

Each spectral band selection subset GML result was entered into a confusion matrix which was used to compute a simple accuracy value. The subsets within an image group were then ranked from 1 to 3, where 3 corresponded to the best results, 2 corresponded to average results, and 1 corresponded to sub-average results. Rankings were based on the sample mean and standard deviation. Subsets assigned a 3 had GML simple accuracy values greater than ½ standard deviation above the mean, while those assigned a 1 had values less than ½ standard deviation below the mean. This method was found to approximate an equal distribution between the three rankings.

The SCR and LOG results were used to construct a stimuli/response matrix as discussed in Section (4.3.3). The probabilities of detection and false alarm for each spectral band subset were used to construct ROC curves. The ROC curves were compared based on the difference between the sum of the probabilities of detection and the sum of the probabilities of false alarm. Since an ideal target detector boasts a 100 percent probability of detection (value of 1) and a zero percent probability of false alarm (value of 0), those spectral band subsets with the greatest summed difference between the probabilities of detection and the probabilities of false alarm should be the best target detectors. As with the GML simple accuracies, the subsets within an image group were ranked from 1 to 3, where rankings were based on the sample mean and standard deviation. Subsets assigned a 3 had difference values greater than ½ standard deviation above the mean, while those assigned a 1 had values less than ½ standard deviation below the mean. This method was found to approximate an equal distribution between the three rankings.

The spectral band subset rankings were then entered into appropriate matrices so that direct comparisons between band selection techniques and input parameter sets could be made across the range of images and classification methods. The complete results are shown in Appendix A.

6.1 Band Selection Results

6.1.1 Tank Scene

The two-band subset selection results for the *tank* scene are shown in Table (6). The image spectral band set was initially reduced from fifteen to five bands using the Eigenvector Pre-Selection technique. In this case, the first pre-selection subset was based on the target/background ROI's, whereas the second pre-selection subset was based on the class2 ROI's. It is interesting to note that the initial pre-selection outputs share only two of the five selected bands. This indicates that the landcover ROI's and the tg/bg ROI's differed significantly in their respective spectral characteristics. It is also interesting to note that the output subsets for the original and modified Thresholded Divergence techniques differ for most of the input parameter sets. In these cases, the input parameter sets must have produced d_{ratio} values greater than one.

Table 6: Tank scene 2-band results

p1/tg	TD orig/p1/clas1	TD mod/p1/clas1	fsbs/p1/clas1
1	1	1	3
3	9	3	9
4	TD orig/p1/clas2	TD mod/p1/clas2	fsbs/p1/clas2
7	4	1	3
9	7	3	9
	TD orig/p2/clas2	TD mod/p2/clas2	fsbs/p2/clas2
	3	3	3
p2/clas2	9	9	9
3	TD orig/p2/tg	TD mod/p2/tg	fsbs/p2/tg
9	3	3	3
12	15	9	12
14	TD orig/p1/tg	TD mod/p1/tg	fsbs/p1/tg
15	1	1	1
	3	3	3
	sbf/p1	sbf/p2	sbf/full
	3	3	3
	9	15	15
	pre-select/clas1	pre-select/clas2	pre-select/tg
	14	14	1
	15	15	3

The 4-band results for the *tank* scene are shown in Table (7). In this case, the fifteen band image spectral band set was initially reduced to eight bands using the eigenvector pre-selection. The two subsets share six of the eight bands. Calculations find the correlation coefficients between bands 6 and 7 to be 0.986, and between bands 12 and 13 to be 0.998. Such values approaching unity indicate that any differences between the subsets should be negligible. With this in mind, then, we should expect to see similar end classification accuracies for spectral subsets which differ only slightly. One example of a group of similar subsets includes TD mod/p1/class1, TD mod/p1/class2, and TD mod/p2/class2. Subsequent down-selects using the band selection techniques under evaluation do not indicate any clear trends between techniques or input parameters with respect to this image.

Table 7: Tank scene 4-band results

p1/tg	TD orig/p1/clas1	TD mod/p1/clas1	fsbs/p1/clas1
1 9	1 12	1 7	3 9
3 12	4 14	3 12	6 12
4 14	TD orig/p1/clas2	TD mod/p1/clas2	fsbs/p1/clas2
7 15	1 9	1 7	3 9
	7 14	3 12	7 14
	TD orig/p2/clas2	TD mod/p2/clas2	fsbs/p2/clas2
	1 9	1 6	3 9
p2/clas2	6 14	3 13	6 12
1 9	TD orig/p2/tg	TD mod/p2/tg	fsbs/p2/tg
3 13	4 9	1 4	1 4
4 14	6 13	3 15	3 6
6 15	TD orig/p1/tg	TD mod/p1/tg	fsbs/p1/tg
	4 7	1 4	1 4
	9 13	3 15	3 7
TD orig/full	sbf/p1	sbf/p2	sbf/full
2 14	3 14	3 14	3 11
4 15	9 15	9 15	9 15
FSBS/full	pre-select/clas1	pre-select/clas2	pre-select/tg
3 9	3 14	3 14	1 7
6 14	9 15	6 15	3 9

6.1.2 Desert Scene

The *desert* scene 2- band results are shown in Table (8). In this case, five-band pre-selection subsets of the ten-band image spectral band set were identical for both the target and class2 ROI sets. This result indicates that the image as a whole must demonstrate less statistical variation then the previously discussed tank scene. In addition, based on this result, we should not expect substantial variation between band selection techniques or between input parameter sets in subsequent down-selects. The results in Table (8) validate this expectation. The thresholded divergence original and

Table 8: Desert scene 2-band results

p1/tg	TD orig/p1/clas1	TD mod/p1/clas1	fsbs/p1/clas1
1	3	3	7
3	7	7	10
7	TD orig/p1/clas2	TD mod/p1/clas2	fsbs/p1/clas2
9	3	3	7
10	7	7	10
	TD orig/p2/clas2	TD mod/p2/clas2	fsbs/p2/clas2
	****	****	****
p2/clas2	****	****	****
	TD orig/p2/tg	TD mod/p2/tg	fsbs/p2/tg
P1=p2			
	****	****	****
	****	****	****
	TD orig/p1/tg	TD mod/p1/tg	fsbs/p1/tg
	1	1	1
	10	10	10
	sbf/p1	sbf/p2	sbf/full
	3	****	3
	9	****	9
	pre-select/clas1	pre-select/clas2	pre-select/tg
	3	3	3
	7	7	7

modified techniques produce identical band sets for each set of input parameters, indicating that the threshold value was sufficient for all input parameter sets. Forward sequential band selection joins thresholded divergence original and modified in producing the same result for class1 and class2 ROI sets.

The *desert* scene 4-band results follow this same trend, although with slightly less uniformity. Once again, the initial down-selects from ten bands to eight bands using eigenvector pre-selection are identical for the target and class2 ROI's. The subsequent down-selects for TD orig , TD mod, and FSBS are nearly identical for class1 and class2

Table 9: Desert scene 4-band results

p1/tg	TD orig/p1/clas1	TD mod/p1/clas1	fsbs/p1/clas1
1 7	3 8	3 7	2 7
2 8	5 10	5 8	5 10
3 9	TD orig/p1/clas2	TD mod/p1/clas2	fsbs/p1/clas2
5 10	3 8	3 7	3 7
	5 10	5 10	5 10
	TD orig/p2/clas2	TD mod/p2/clas2	fsbs/p2/clas2
	****	****	****
p2/clas2	****	****	****
	TD orig/p2/tg	TD mod/p2/tg	fsbs/p2/tg
P1=p2			
	****	****	****
TD orig/full	****	****	****
5 8	TD orig/p1/tg	TD mod/p1/tg	fsbs/p1/tg
6 10	1 7	2 9	1 8
	3 10	5 10	7 10
FSBS/full	sbf/p1	sbf/p2	sbf/full
4 8	1 7	****	3 7
7 10	3 9	****	4 9
	pre-select/clas1	pre-select/clas2	pre-select/tg
	1 7	1 7	1 7
	3 9	3 9	3 10

ROI's. Analysis reveals the correlation coefficient between bands 2 and 3 to be 0.991, and between bands 8 and 10 to be 0.747. We should not expect to observe significant differences between end classification accuracies for the various band selectors within the same input parameter set.

6.1.3 Panel Scene

Eigenvector pre-selection was used on the *panel* scene to initially select ten bands from the original 210-band image spectral band set. The results shown in Table (10) indicate that six of the ten bands are shared, indicating greater statistical variation than we saw in the desert scene. Thus, the increased variability in subsequent down-selection using the band selectors under evaluation is not unexpected. No clear trends across band selection techniques or input parameter sets are immediately evident in the data.

Table 10: Panel scene 2-band results

p1/clas1		TD orig/p1/clas1	TD mod/p1/clas1	fsbs/p1/clas1
1	46	1	64	42
3	54	119	119	119
4	63	TD orig/p1/clas2	TD mod/p1/clas2	fsbs/p1/clas2
7	64	54	64	42
9	119	63	119	119
		TD orig/p2/clas2	TD mod/p2/clas2	fsbs/p2/clas2
		42	54	42
p2/clas2		54	60	54
1	46	TD orig/p2/tg	TD mod/p2/tg	fsbs/p2/tg
2	54	4	62	4
3	60	42	64	42
4	62	TD orig/p1/tg	TD mod/p1/tg	fsbs/p1/tg
42	64	63	63	7
		64	64	42
		sbf/p1	sbf/p2	sbf/full
		63	60	****
		64	64	****
		pre-select/clas1	pre-select/clas2	pre-select/tg
		42	42	54
		64	64	64

The *panel* scene 4-band results shown in Table (11) are based on the same initial eigenvector pre-selection output subsets. In this case, several observations are of interest. Each of the TD original, TD modified, and FSBS subsets are identical for the p1/class1 and p1/class2 input parameter sets, indicating little statistical variation between the two ROI sets within the p1 spectral band subset. However, the significant variation between subsets resulting from the p2/class2, p1/class2, and p1/tg input parameter sets reinforces the expectation of statistical variability previously arrived at based on the 2-band *panel* scene results. It is also interesting to note that the optimal two band subset is not necessarily incorporated into the best four band subset.

Table 11: Panel scene 4-band results

p1/clas1	TD orig/p1/clas1	TD mod/p1/clas1	fsbs/p1/clas1
1 46	3 63	1 64	42 64
3 54	54 119	7 119	54 119
7 63	TD orig/p1/clas2	TD mod/p1/clas2	fsbs/p1/clas2
42 64	3 63	1 64	42 64
45 119	54 119	7 119	54 119
	TD orig/p2/clas2	TD mod/p2/clas2	fsbs/p2/clas2
	2 60	54 62	42 54
p2/clas2	54 64	60 64	46 62
1 46	TD orig/p2/tg	TD mod/p2/tg	fsbs/p2/tg
2 54	2 60	54 62	42 54
3 60	54 64	60 64	46 62
4 62	TD orig/p1/tg	TD mod/p1/tg	fsbs/p1/tg
42 64	7 46	45 54	1 42
	42 63	46 64	7 119
	sbf/p1	sbf/p2	sbf/full
	42 63	46 62	****
	46 64	60 64	****
	pre-select/clas1	pre-select/clas2	pre-select/tg
	****	****	****
	****	****	****

6.1.4 Pasture Scene

The *pasture* scene 2-band eigenvector pre-selection subsets were constructed differently than those of the previous images. In this case, the subsets were based on class1 and class2 ROI's, where the class1 ROI-based set was a twenty band subset of the original 210 spectral bands. The class2-based set was a ten band subset, all of which were members of the class1 ROI-based subset. It is interesting to note that, in this case, the TD orig and TD mod produce identical results for each input parameter set. This indicates that the input threshold value was sufficient and no calculated d_{ratio} values were greater than one. Correlation analysis found the correlation coefficients to be 0.918 between bands 61 and 62, 0.955 between bands 62 and 63, 0.999 between bands 53 and 54, and 0.996 between bands 83 and 84. Such values approaching 1.0 indicate that similar bands sets should produce equivalent end classification accuracies.

Table 12: Pasture scene 2-band results

p1/clas1	TD orig/p1/clas1	TD mod/p1/clas1	fsbs/p1/clas1
1 8 57 65	71	71	55
2 37 61 66	84	84	84
3 53 62 70	TD orig/p1/clas2	TD mod/p1/clas2	fsbs/p1/clas2
4 54 63 71	57	57	55
5 55 64 84	61	61	84
	TD orig/p2/clas2	TD mod/p2/clas2	fsbs/p2/clas2
	57	57	61
p2/clas2	61	61	83
1 57	TD orig/p2/tg	TD mod/p2/tg	fsbs/p2/tg
3 61	63	63	62
53 62	83	83	83
54 63	TD orig/p1/tg	TD mod/p1/tg	fsbs/p1/tg
55 83	66	66	62
	70	70	84
	sbf/p1	sbf/p2	sbf/full
	53	53	61
	54	54	71
	pre-select/clas1	pre-select/clas2	pre-select/tg
	54	54	54
	71	83	64

The 4-band results are shown in Table (13). The 10-band eigenvector pre-selection output is a subset of the 20-band set used for the *pasture* scene 2-band results. The class2-based set is identical to that used for the *pasture* scene 2-band results. No clear trends are immediately evident in the data.

Table 13: Pasture scene 4-band results

p1/clas1	TD orig/p1/clas1	TD mod/p1/clas1	fsbs/p1/clas1
1 55	3 63	54 62	54 61
3 61	53 71	61 71	55 71
4 62	TD orig/p1/clas2	TD mod/p1/clas2	fsbs/p1/clas2
53 63	1 53	55 62	54 61
54 71	3 71	61 71	55 71
	TD orig/p2/clas2	TD mod/p2/clas2	fsbs/p2/clas2
	1 54	57 62	54 61
p2/clas2	3 83	61 83	57 83
1 57	TD orig/p2/tg	TD mod/p2/tg	fsbs/p2/tg
3 61	3 63	3 63	57 63
53 62	54 83	62 83	62 83
54 63	TD orig/p1/tg	TD mod/p1/tg	fsbs/p1/tg
55 83	3 63	3 63	54 62
	53 71	62 71	55 71
	sbf/p1	sbf/p2	sbf/full
	61 63	61 63	****
	62 71	62 83	****
	pre-select/clas1	pre-select/clas2	pre-select/tg
	****	****	****
	****	****	****

6.2 Comparison between Band Selectors by Image

Two and Four-Band Case

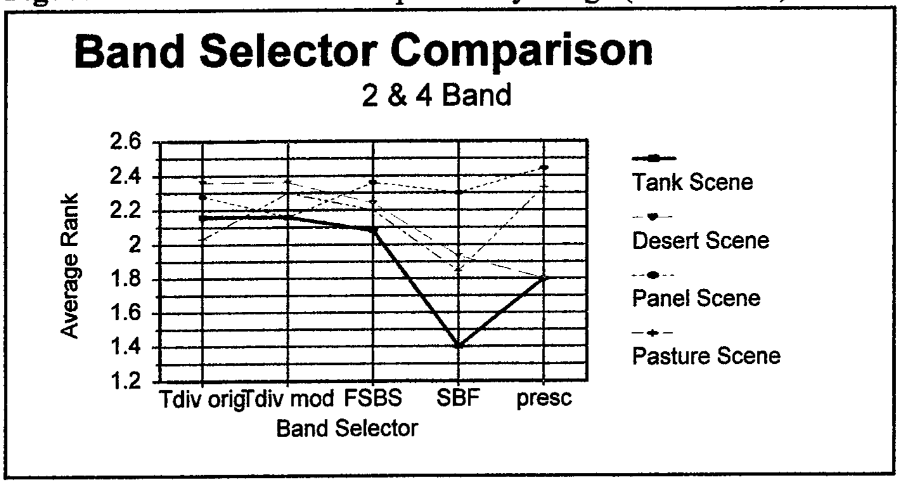
The band selector comparison mean rank and standard deviation of the ranks for each image across the classifiers and input parameter sets for the combined 2 and 4-band cases are listed in Table (14) and plotted in Figure (24). The standard deviation values are based on approximately twenty samples. From this data, we can see that the original and modified versions of thresholded divergence produce the strongest average rank for both the tank and desert scenes across the range of classifiers and input parameter sets.

Table 14: Band Selector Comparison Results (2 & 4 Band)

	TD Orig (avg rank/ std)	**TD Mod** (avg rank/ std)	**FSBS** (avg rank/ std)	**SBF** (avg rank/std)	**Pre-Select** (avg rank/ std)
Tank	2.16 / 0.800	2.16 / 0.898	2.08 / 0. 909	1.40 / 0.507	1.80 / 0.775
Desert	2.36 / 0.700	2.36 / 0.700	2.28 / 0.723	1.93 / 0.704	1.80 / 0.775
Panel	2.28 / 0.678	2.16 / 0.746	2.36 / 0.700	2.30 / 0.823	2.31 / 0.751
Pasture	2.03 / 0.718	2.30 / 0.651	2.20 / 0.805	1.85 / 0.689	2.15 / 0.899

Due to the fundamental similarities between the two thresholded divergence variations, it is not surprising that, given the appropriate data set, the two average ranks are nearly identical. The difference between the two methods is rooted in the original thresholded divergence stipulation (Rosenblum, 1990) which states that any values for d_{ratio} greater than 1.0 are set equal to 1.0. Where the selected threshold value is sufficiently large, this

Figure 24: Band Selector Comparison by Image (2 & 4 Band)



methodical difference should not be an issue. This is likely the situation we see for the *tank* and *desert* results in Table (14). However, where the selected threshold value is not sufficiently large given the input parameters, this one condition can affect the end spectral band subset selection. By rendering equal all values for d_{ratio} greater than 1.0 regardless of the actual distance, it is possible for a band subset with a greater actual summed distance to be overlooked in favor of another subset with lower above-threshold ratio values. This phenomenon is a likely explanation for the lower average rank offered by the original TD method for the *pasture* scene. At the same time, allowing values for d_{ratio} greater than 1.0 to retain their true value can permit inflation of the value for the sum of all distances between classes (equation) so that inordinately low values are averaged with high values, thereby resulting in a false-high sum and subsequent selection of a sub-optimal spectral band set. This is likely the reason why the modified TD average rank is significantly lower than the original TD average rank for the *panel* scene. It is this conflict which may result in inconsistencies between the two techniques. Relatively high standard deviation values indicate non-negligible variability within the spectral band selection results for each method.

While FSBS serves as the top overall performer for the *panel* scene and TD Mod performs well for the *pasture* scene, eigenvector pre-selection used as a full band selector is clearly revealed to be a strong performer for both the *panel* and *pasture* scenes. Eigenvector pre-selection is based on principal components analysis (PCA) in which the early eigenvectors exhibit the largest variance. In hyperspectral imagery such as the *panel* and *pasture* scenes, we expect a high degree of correlation between bands. Thus, sufficient down-selection using PCA should prove effective in identifying those bands with the greatest overall variance which, in turn, should prove to be the same bands for which the distance between class means is greatest. Since all of the classifiers are in some form dependent on the distance between class means, those bands selected via eigenvector pre-selection, assuming a sufficiently small subset, should produce high classification accuracies. Additional observation reveals that the pre-selection technique boasts the lowest standard deviation of the average rank for the *panel* scene.

In the 2 and 4-band combined data set, we do not see a clear trend based on image type; while the M7 images demonstrate the best overall response to the thresholded divergence methods, the Hydice imagery does not consistently respond well to any one band selection technique.

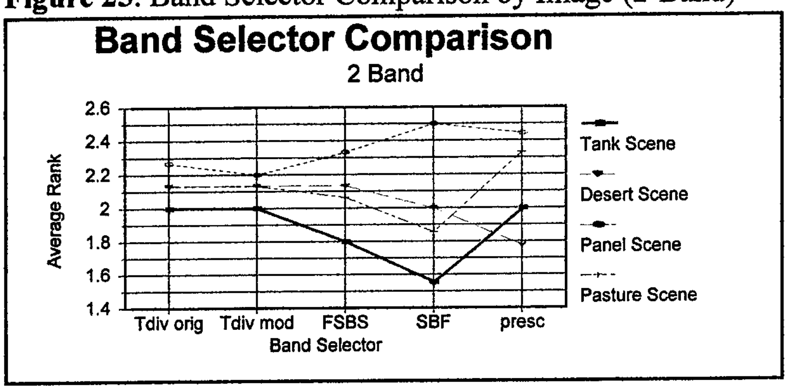
Two Band Case

The 2-band results shown in Table (15) and Figure (25) differ from those for the two and four band combined case, thereby implying a subset-size rather than an image-type dependence. For the *tank* scene, the thresholded divergence methods and eigenvector pre-selection share the best average rank, although eigenvector pre-selection appears to have the least variability within the data based on the standard deviation value.

Table 15: Band Selector Comparison Results (2-Band)

	TD Orig (avg rank/ std)	**TD Mod** (avg rank/ std)	**FSBS** (avg rank/ std)	**SBF** (avg rank/std)	**Pre-Select** (avg rank/ std)
Tank	2.00 / 0.845	2.00 / 0.926	1.80 / 1.014	1.55 / 0.527	2.00 / 0.707
Desert	2.13 / 0.743	2.13 / 0.743	2.20 / 0.414	2.00 / 0.866	1.78 / 0.972
Panel	2.26 / 0.594	2.20 / 0.676	2.33 / 0.724	2.00 / 0.837	2.55 / 0.527
Pasture	2.13 / 0.743	2.13 / 0.743	2.06 / 0.799	1.86 / 0.690	2.33 / 0.866

Figure 25: Band Selector Comparison by Image (2-Band)



Eigenvector pre-selection as a strong technique seems logical given the subset size and input parameter set. As with the Hydice imagery in the 2 and 4-band case, it is possible that the ROI's are sufficiently well-defined and the subset size sufficiently small so that eigenvector pre-selection is able to adequately identify those bands with the greatest variance, which, in this case, corresponds to the greatest distance between class means. In contrast, forward sequential band selection demonstrates the highest average rank with the lowest variability for the *desert* scene. This result is likely due to the lower level of scene diversity within the image from with ROI's could be constructed and used for eigenvector definition. Despite these differences, it is apparent that the thresholded divergence techniques again produce solid, if not optimal, results for both of the M7 images.

The two-band data set reveals that the Hydice imagery responded best to simple Eigenvector Pre-Selection. This trend is likely due to the nature of the image-type spectral bands. The Hydice imagery with narrower bandwidths and near-continuous coverage from 0.4 to 2.5 μm is expected to demonstrate higher correlation between bands and thus prove more responsive to eigenvector pre-selection than the M7 images with fewer, wider, and non-continuous bandwidths.

Four-Band Case

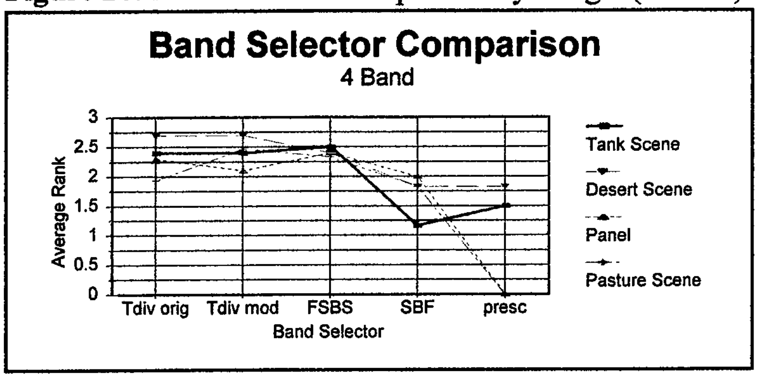
As with 2-band or the 2 and 4-band combined image data, no clear trend seems to exist between image or scene type and band selector for the 4-band case. From Table (16) and Figure (26), we see that forward sequential band selection produced the highest average rank for the *tank* and *panel* scenes, while the *desert* and *pasture* scenes responded better

Table 16: Band Selector Comparison Results (4-Band)

	TD Orig (avg rank/ std)	**TD Mod (avg rank/ std)**	**FSBS (avg rank/ std)**	**SBF (avg rank/std)**	**Pre-Select (avg rank/ std)**
Tank	2.40 / 0.699	2.40 / 0.843	2.50 / 0.527	1.16 / 0.408	1.50 / 0.836
Desert	2.70 / 0.483	2.70 / 0.483	2.40 / 0.966	1.83 / 0.408	1.83 / 0.408
Panel	2.30 / 0.823	2.10 / 0.875	2.40 / 0.699	2.00 / 0.816	1.75/0.957
Pasture	1.93 / 0.704	2.46 / 0.516	2.33 / 0.816	1.83 / 0.753	1.75/0.957

to the thresholded divergence methods. In addition, for both the *tank* and the *panel* scenes, forward sequential band selection resulted in the lowest variability within the respective data sets. That the highest average rank for the tank scene swapped from the thresholded divergence methods for the 2-band case to FSBS for the 4-band case, while for the *desert* scene, the highest average rank reverse-swapped from FSBS for the 2-band

Figure 26: Band Selector Comparison by Image (4-Band)



case to the thresholded divergence methods for the 4-band case indicates a greater dependence on subset size than image type for the thresholded divergence and FSBS band selectors. This observation is supported by the eigenvector pre-selection technique's drop for the tank scene from a top band selector for the 2-band case to a sub-average band selector for the 4-band case.

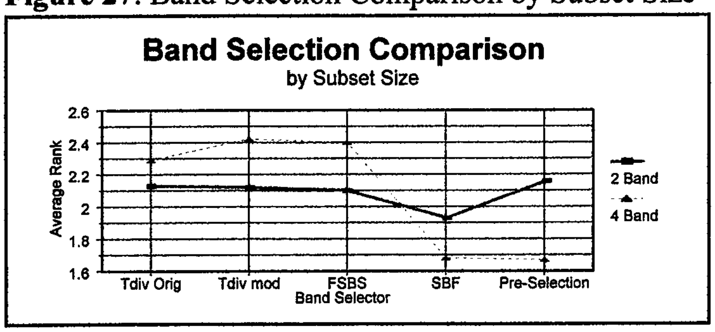
6.3 Comparison by Number of Bands

The mean rank and standard deviation for each band selection technique across the range of scenes and input parameter sets shown in Table (17) and Figure (27) support the subset-size dependency identified above. The data indicate a clear shift from eigenvector pre-selection as the top overall performer for the 2-band case to the modified thresholded divergence and FSBS techniques for the 4-band case. That eigenvector pre-selection deteriorates with increased subset size is not surprising. As the subset size increases, the lower-level eigenvectors included in the selection by pre-selection have lower variance and are less likely to directly correspond to the bands which maximize the distance between class means.

Table 17: Band Selector Comparison by Number of Bands

	TD Orig (avg rank/ std)	**TD Mod** (avg rank/ std)	**FSBS** (avg rank/ std)	**SBF** (avg rank/std)	**Pre-Select** (avg rank/ std)
2 Band	2.13 / 0.724	2.12 / 0.761	2.10 / 0.787	1.93 / 0.772	2.16 / 0.798
4 Band	2.29 / 0.727	2.42 / 0.690	2.40 / 0.751	1.68 / 0.646	1.70 / 0.651

Figure 27: Band Selection Comparison by Subset Size



6.4 Comparison by Classifier

Based on theory, it is expected that both the Gaussian maximum likelihood and signal-to-clutter ratio classifiers should respond best to spectral band subsets selected by the thresholded divergence techniques. This seems logical since all three techniques are based on the multivariate distance between class means as determined by the Mahalanobis distance. The log-likelihood classifier, which is based on related Bayesian

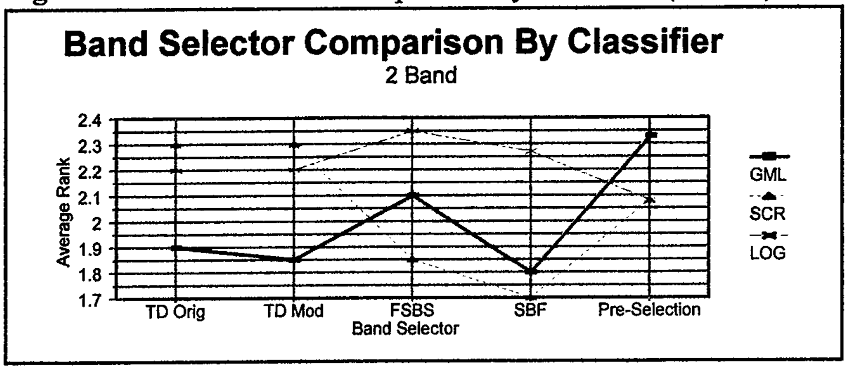
Table 18: Band Selector Comparison Results by Classifier (2 Band)

	TD Orig (avg rank/ std)	**TD Mod** (avg rank/ std)	**FSBS** (avg rank/ std)	**SBF** (avg rank/std)	**Pre-Select** (avg rank/ std)
GML	1.90 / 0.641	1.85 / 0.671	2.10 / 0.788	1.80 / 0.632	2.33 / 0.778
SCR	2.30 / 0.571	2.30 / 0.657	1.85 / 0.671	1.70 / 0.675	2.08 / 0.900
LOG	2.20 / 0.894	2.20 / 0.894	2.35 / 0.813	2.27 / 0.904	2.08 / .793

statistics should respond well to either thresholded divergence or the Bayesian-based forward sequential band selector.

The results shown in Tables (18), (19), and (20) as well as Figures (28), (29), and (30) reveal both subset-size and classifier-type dependencies. Gaussian maximum likelihood responds best to the eigenvector pre-selection subset for the 2-band case. For the 4-band case, however, the eigenvector pre-selection subset results in a sub-average response, while the original thresholded divergence subset provides the highest average rank. As

Figure 28: Band Selector Comparison by Classifier (2 Band)



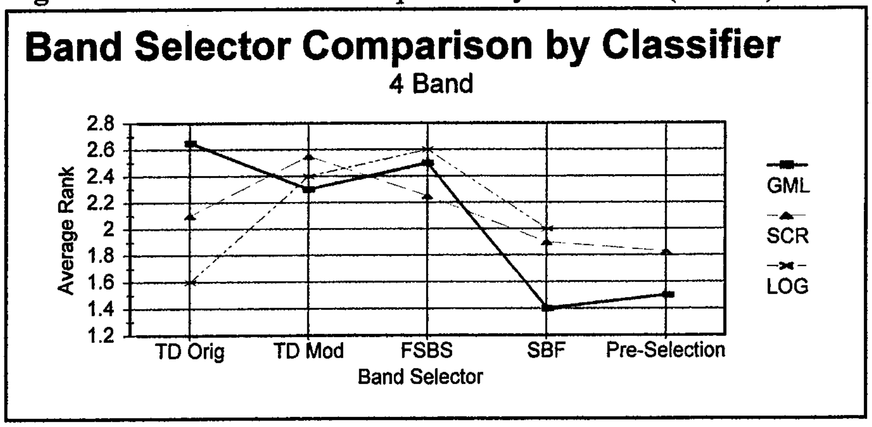
in previous comparisons, the decreasing success of eigenvector pre-selection with increased subset-size seems logical since the latter principal components display less variance which can be directly translated to multivariate distance between class means than their earlier counterparts. It is interesting to note that while FSBS is not a top performer in either the 2-band or the 4-band case, it surfaces as the best overall performer when used in conjunction with GML classification for the 2 and 4-band case.

The signal-to-clutter ratio results experience a less drastic change as the subset size is increased. Unlike its GML counterpart, SCR demonstrates the strongest response to both

Table 19: Band Selector Comparison Results by Classifier (4 Band)

	TD Orig (avg rank/ std)	**TD Mod** (avg rank/ std)	**FSBS** (avg rank/ std)	**SBF** (avg rank/std)	**Pre-Select** (avg rank/ std)
GML	2.65 / 0.489	2.30 / 0.733	2.50 / 0.761	1.40 / 0.516	1.70 / 0.823
SCR	2.10 / 0.788	2.55 / 0.686	2.25 / 0.786	1.90 / 0.738	1.70 / 0.675
LOG	1.60 / 0.548	2.40 / 0.548	2.60 / 0.548	2.00 / 0.000	****

Figure 29: Band Selector Comparison by Classifier (4 Band)

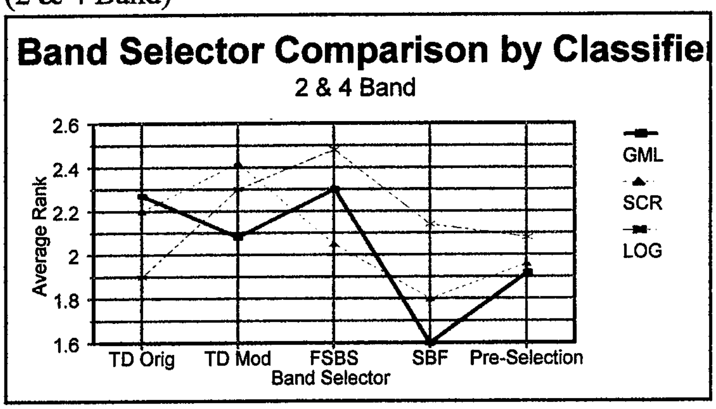


of the thresholded divergence output band subsets for the 2-band case. As the subset size is increased to 4 bands, the modified thresholded divergence result remains strong, while the original thresholded divergence result slips. This effect is due to insufficient threshold values for the 4-band input parameter sets. Nearly identical average ranks for the 2-band case indicate that the threshold values were sufficient for subset determination using the original TD technique. The non-negligible difference between the original and modified TD average ranks for the 4-band case indicates that some subsets selected by the modified TD technique must have had d_{ratio} values greater than 1.0 which were set equal to 1.0 and thus not identified as optimal. (See Section 4.1.3) Overall, for the 2 and 4-band case, the modified TD technique demonstrated the highest average rank when used in conjunction with the signal-to-clutter ratio classifier.

Table 20: Band Selector Comparison Results by Classifier (2 & 4 Band)

	TD Orig (avg rank/ std)	**TD Mod** (avg rank/ std)	**FSBS** (avg rank/ std)	**SBF** (avg rank/std)	**Pre-Select** (avg rank/ std)
GML	2.27 / 0.679	2.08 / 0.730	2.30 / 0.791	1.60 / 0.621	2.02 / 0.800
SCR	2.20 / 0.687	2.42 / 0.675	2.05 / 0.749	1.80 / 0.696	1.89 / 0.840
LOG	1.90 / 0.862	2.30 / 0.831	2.48 / 0.764	2.14 / 0.835	2.08 / 0.793

Figure 30: Band Selector Comparison by Classifier (2 & 4 Band)



In contrast to the results for the other classifiers, we see little subset-size dependency with log-likelihood classification. It is clear from Tables (18), (19), and (20) that the FSBS output subsets demonstrate the highest average ranks for the 2-band, 4-band, and 2 and 4-band cases. It is interesting to note, however, that the average rank for the original thresholded divergence output subsets experienced a decrease with increased subset size similar to that observed for signal-to-clutter classification.

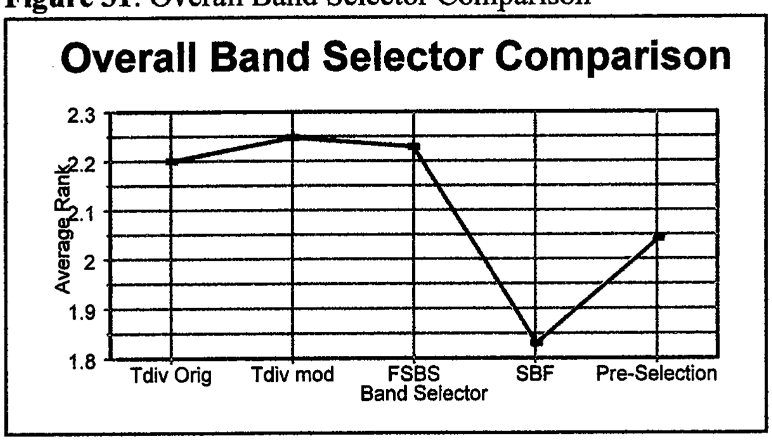
6.5 Overall Band Selector Comparison Results

The average ranks for the overall band selector comparison were calculated by averaging all of the ranks for each image, classifier, and input parameter subset for a given spectral band selection technique. The results are shown in Table (21) and Figure (31). The data indicate little difference in both average rank and standard deviation across the range of scenes, classification techniques, and input parameter sets between the original thresholded divergence, modified thresholded divergence, and forward sequential band selection techniques.

Table 21: Overall Band Selector Comparison Results

TD Orig (avg rank/ std)	TD Mod (avg rank/ std)	FSBS (avg rank/ std)	SBF (avg rank/std)	Pre-Select (avg rank/ std)
2.20 / 0.726	2.25 / 0.744	2.23 / 0.794	1.83 / 0.727	2.00 / 0.798

Figure 31: Overall Band Selector Comparison



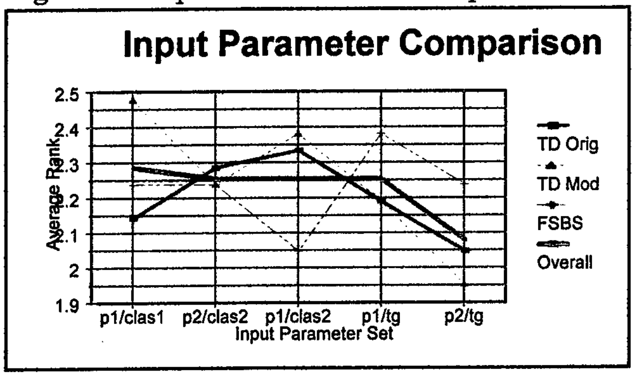
6.6 Comparison between Input Parameter Sets

From previous analysis, we know that forward sequential band selection and both the original and modified thresholded divergence techniques provide roughly equivalent average results across a range of scenes, image types, classifiers, and input parameter sets. With these band selectors in mind, the next question is whether any one input parameter set or sequence of input parameters provides better average results. The data shown in Table (22) and Figure (32) suggest that, although the individual band selector techniques do exhibit input parameter dependencies, no one input parameter set stands out across the range of band selectors. It is clear, however, that for each individual band selector, the optimal input parameter set was based on p1, the initial eigenvector pre-selection subset built using the class1 ROI set. Neither of the input parameter sets incorporating p2, the initial eigenvector pre-selection subset built using the class2 ROI set, result in a high average ranking for any individual band selector. Based on this observation, it seems that for any image type or band selector, best overall results are obtained using an initial down-select constructed from the most generic regions of interest.

Table 22: Input Parameter Set Comparison Results by Band Selector (2 & 4 Band)

	p1/clas1 (avg rank)	**p2/clas2** (avg rank)	**p1/clas2** (avg rank)	**p1/tg** (avg rank)	**p2/tg** (avg rank)
TD Orig	2.14	2.28	2.33	2.19	2.05
TD Mod	2.48	2.24	2.38	2.19	1.95
FSBS	2.24	2.24	2.05	2.38	2.24
Overall	2.29	2.25	2.25	2.25	2.08

Figure 32: Input Parameter Set Comparison



6.7 Stratified Random Sampling Results

Classification accuracies were re-examined for a subset of the original band selection data set using stratified random sampling techniques in conjunction with GML and SCR classification. Previous analysis in Section (6.5) revealed that Forward Sequential Band Selection, and the original and modified Thresholded Divergence techniques produce similar results across the range of scene types, classification techniques, and input parameter sets. It was additionally found in Section (6.6) that each of the aforementioned band selection techniques performed best with a different input parameter set. Based on these results, the following input parameter sets were selected for further evaluation: Original Thresholded Divergence using p1 and class2, Modified Thresholded Divergence using p1 and class1, and Forward Sequential Band Selection using p1 and tg. The *tank* and *desert* scenes were used for the additional analysis.

The classification accuracies based on GML classification for both images and each of the selected subsets are shown in Table (23). As expected, the classification accuracies are lower for the stratified random sampling results. This can be attributed to the random

Table 23: GML Stratified Random Sampling Accuracy Assessment

Image	Input Parameter Set	Independent Analysis (% Accuracy)	Stratified Sampling (% Accuracy)
Tank Scene	TDorig/p1/class2	92.3	71.0
	TDmod/p1/class1	89.7	55.0
	FSBS/p1/tg	89.7	55.0
Desert Scene	TDorig/p1/class2	85.3	56.19
	TDmod/p1/class1	85.3	56.19
	FSBS/p1/tg	81.1	63.11

nature of pixel selection and user error; ambiguous pixels not clearly belonging to any one class were selected for analysis. For the *tank* scene results, the TD orig/p1/class2 input parameter set produced better results for both independent analysis and stratified random sampling accuracy assessment techniques. The TD mod/p1/class1 and FSBS/p1/tg spectral band subsets were identical in this case. The *desert* scene stratified random sampling results, on the other hand, were not consistent with the independent analysis results. Using independent analysis, the TD methods performed better than FSBS, while for stratified random sampling, the reverse was true. Despite this discrepancy, however, in both cases the difference between the output accuracies is within a few percentage points and can, therefore, be considered negligible.

The classification accuracies based on SCR classification for both images and each of the selected subsets are shown in Table (24). In this case, the stratified random sampling results exactly match the independent analysis results for all input parameter sets for both images. This result is likely due to reduced ambiguities between target and background spectral characteristics; where some landcover classes can appear nearly indistinguishable either visually to the user or spectrally to the algorithm, target pixels are typically more distinct.

Table 24: SCR Stratified Random Sampling Accuracy Assessment

Image	Input Parameter Set	Independent Analysis (% hit-false alarm)	Stratified Sampling (% hit-false alarm)
Tank Scene	TDorig/p1/class2	-0.47	-0.47
	TDmod/p1/class1	1.0	1.0
	FSBS/p1/tg	1.0	1.0
Desert Scene	TDorig/p1/class2	1.85	1.85
	TDmod/p1/class1	1.85	1.85
	FSBS/p1/tg	-0.23	-0.23

In both cases, the stratified random sampling and independent analysis results are similar. This similarity seems to imply that the independent analysis results can be considered accurate across the range of images and spectral band subsets. Any conclusions based on independent analysis results, then, can also be considered reliable.

6.8 Correlation Analysis

A final examination focused on existing or potential correlations between Gaussian Maximum Likelihood, Signal-to-Clutter Ratio, and Log-Likelihood Test Ratio classification accuracies. Linear regression was performed using the rank values for each input parameter set for each image with R Squared, the square of the correlation between the two input variables, as the output. An R Squared value of 1.0 indicates perfect correlation, which a value approaching zero indicates low correlation between the input data sets. Results shown in Table (25) indicate the greatest correlation between GML and SCR classification accuracies. This seems logical since both GML and SCR are based on similar multivariate statistics. Despite this association, however, none of the calculated R Squared values indicate any significant correlation between classification techniques.

Table 25: Correlation Analysis

Number of Bands	Data Sets	R^2
2 Band	GML/SCR	0.034
	GML/LOG	0.00069
	SCR/LOG	0.00067
4 Band	GML/SCR	0.0013

7.0 Summary and Conclusions

The goal of this research was to determine if any one pre-existing band selection technique could consistently perform well across a range of images, exploitation algorithms, and input parameter sets so that end classification results based on spectral band subsets selected without specific *a priori* information would be reasonable, if not optimal. Test images were selected to provide a range of landcover and target types. Regions of interest were constructed specifically to stress each of the band selection algorithms chosen for evaluation. Accuracy assessment was based on stratified random sampling as well as independent analysis in an effort to verify the results upon which these conclusions are based.

Overall band selector comparison results suggest that, across the range of scenarios and classifiers, the Thresholded Divergence and Forward Sequential Band Selection techniques produce roughly equivalent, average results surpassing those of Eigenvector Pre-Selection and Spectral Basis Functions. No one band selection technique stands out, which is not unexpected in consideration of the similar statistical foundations from which the aforementioned band selectors were developed; both Thresholded Divergence and Forward Sequential Band Selection are based upon the multivariate distance between class means, and both take into account the influence of individual class covariance matrices.

Further analysis, however, provided insight into the extent to which spectral band subset-size, image and scene-type, classifier-type, and input training regions impact individual band selector performance. Spectral band subset size immediately surfaced as a potentially significant influence. While the overall performance of Thresholded

Divergence and Forward Sequential Band Selection improved, Eigenvector Pre-Selection and Spectral Basis Functions performance declined with increased subset size. With this in mind, then, it seems reasonable that *a priori* knowledge of the desired subset size should impact appointment of a spectral band selection technique.

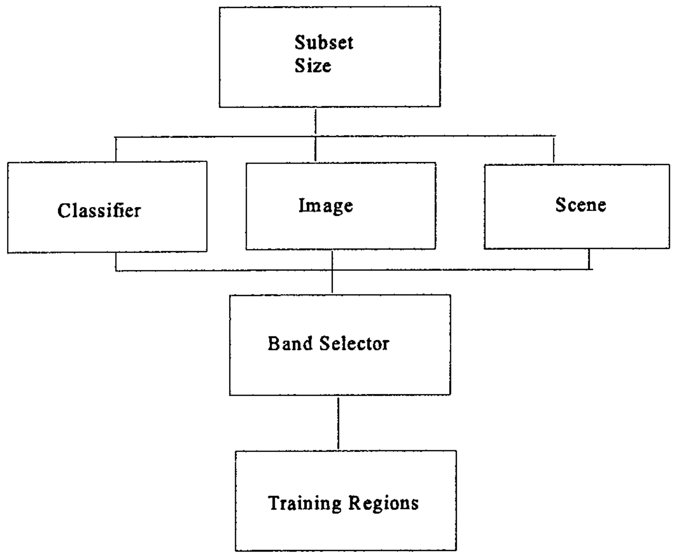
In contrast, results indicate little average rank dependency on image or scene-type. The comparison by image data reveal clear shifts in the relative rankings of the band selectors across the range of imagery for both the 2-band and the 4-band cases. Those shifts are not consistent with either image-type or scene type, however, thereby implying that neither image nor scene-type serves as a determining factor. Instead, the additional shifts in relative rankings which are evident as the subset size is increased from two to four bands point towards subset-size as the greater influence.

A similar conclusion can be made with respect to any potential classifier-type dependencies. Each classifier demonstrates the best average performance with used with a different band selector, and those pairings change as the subset-size changes. Thus, while classifier-type does influence the end classification accuracies, subset size once again serves as the greater influence.

The final parameter which seems to affect average rankings is the input set of training regions and the order in which they are used. Comparison results reveal that each band selector responds best to a different input parameter set. The one commonality across the evaluated band selectors is found in the initial down-select; in each case, the best average performance was obtained when the more generic ROI set was used for initial down-selection. The generic regions of interest must demonstrate greater variances which translate more directly to the multivariate distance between class means used for subsequent band selection. Once initial down-selection is achieved, however, each of the evaluated band selectors performs best with a different ROI set. Thus, it can be said that awareness of the input training regions of interest can influence the end classification accuracy.

Based on these observations and conclusions, it seems that a four-tiered approach, a schematic of which is shown in Figure (33), should produce the best overall end classification accuracies. Spectral band subset size, as the driving factor, has been shown to influence classifier, image, and scene-type dependencies. For this reason, it should be decided upon first. Once subset size is determined, the predicted best spectral band selection technique can be chosen based on any available classifier, image, or scene-type *a priori* information. Finally, training regions can be constructed to maximize the chosen band selector performance.

Figure 33: Spectral Band Selection Approach



8.0 Recommendations for Future Work

This study provided valuable insight into the question of optimal spectral band selection in the absence of *a priori* information. This same insight has raised additional issues worthy of study. The Spectral Basis Functions band selection technique was selected for examination due to its seeming mathematical robustness and lack of specific classification algorithm for which it was intended. In the course of application, however, difficulties were encountered which, coupled with time constraints, mandated a modified approach focused specifically on the method used for initial interval selection. Results obtained using only the initial interval selection technique did not highlight SBF as a strong candidate for optimal band selection. However, it is possible that a more thorough examination of the basis function development and interval refinement techniques might, indeed, reveal SBF to be a viable option for spectral band selection in the absence of *a priori* information.

The subset size for initial down-selection using Eigenvector Pre-Selection was determined primarily based on processing time and input image constraints. It is not known if the subset size used maximized the subsequent down-selection. A worthwhile study could examine the question of how many bands should be pre-selected and passed on to subsequent band selection routines to optimize the end result.

The question of image and scene-type dependencies was addressed in the course of this study. Due to time and processing constraints, the data set was limited to four images. While these images as a group provided a range of landcover and target classes, it is possible that a more robust data set might more clearly demonstrate image or scene-type trends which could be used for selection of the best spectral band selection technique.

It was additionally observed in the course of this study that input training regions and the order in which they are used can significantly impact both band selection and end classification accuracy regardless of the band selection technique. With this in mind, it seems that a more thorough understanding of this phenomena might significantly enhance end results, particularly in the absence of specific *a priori* information.

Finally, several issues not specifically addressed by this study, but worthy of examination arose in the course of discussion. The functionality of each of the band selectors could be assessed when used to identify targets with very specific spectral signatures in a localized region. A very similar study could focus instead on identification of 'hard' targets, targets such as camouflage which are spectrally very similar to the background spectral signature. Any of the aforementioned issues could incorporate an examination of atmospheric effects on band selection and the end classification accuracies.

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10.0 Appendices

Appendix Table of Contents

Appendix A

Table A-1: Tank Scene 2-Band Results

Image Name	TANK		
p1/tg	tdiv orig/p1/clas1	tdiv mod/p1/clas1	fsbs/p1/clas1
3	1	1	3
4	9	3	9
	tdiv orig/p1/clas2	tdiv mod/p1/clas2	fsbs/p1/clas2
	4	1	3
	7	3	9
p2/clas2	tdiv orig/p2/clas2	tdiv mod/p2/clas2	fsbs/p2/clas2
3	3	3	3
9	9	9	9
15	tdiv orig/p2/tg	tdiv mod/p2/tg	fsbs/p2/tg
	3	3	3
	15	9	12
	tdiv orig/p1/tg	tdiv/p1/tg	fsbs/p1/tg
	1	1	1
	3	3	3
	sbf_int/p1	sbf_int/full	
	3	3	
	9	15	
	presc/clas1	presc/tg	
	14	1	
	15	3	

Table A-2: Tank Scene 2 -Band Gaussian Maximum Likelihood Confusion Matrices

Bands 1 3

Truth

	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74	0	0	0	0	0	0	0	0	0	74
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	0	0	73	0	7	0	0	0	0	1	81
Forest	0	0	0	203	0	0	0	0	0	0	203
Driveway	0	0	0	0	50	0	0	0	0	0	50
Sand	14	0	0	0	0	91	0	0	0	0	105
Circle	0	0	0	0	0	0	65	0	8	7	80
NoName	2	0	0	0	0	0	6	45	47	0	100
Sc/Bush	0	0	0	0	0	0	5	3	88	0	96
Sc/Weed	0	0	0	0	0	0	0	0	0	129	129
Total	90	96	73	203	57	91	76	48	143	137	89.6957

RANK 2

9 12

Truth

	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	87	1	0	0	0	0	9	1	0	0	98
Roof	0	80	0	0	0	1	0	0	4	1	86
Road	0	0	71	0	3	0	0	0	0	0	74
Forest	0	0	0	203	0	0	0	0	0	0	203
Driveway	0	0	1	0	54	0	0	0	0	1	56
Sand	0	0	0	0	0	39	0	1	0	0	40
Circle	3	3	0	0	0	0	60	2	0	4	72
NoName	0	3	0	0	0	51	6	44	8	0	112
Sc/Bush	0	0	0	0	0	0	0	0	131	0	131
Sc/Weed	0	9	1	0	0	0	1	0	0	131	142
Total	90	96	73	203	57	91	76	48	143	137	88.3218

2

3 9

Truth

	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	75	0	0	0	0	0	0	0	0	0	75
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	0	0	72	0	6	0	0	0	0	0	78
Forest	0	0	0	202	0	0	0	0	0	0	202
Driveway	0	0	1	0	51	0	0	0	0	0	52
Sand	0	0	0	0	0	85	0	0	0	0	85
Circle	0	0	0	0	0	0	65	0	1	2	68
NoName	0	0	0	0	0	0	1	31	39	5	76
Sc/Bush	15	0	0	1	0	6	8	17	103	0	150
Sc/Weed	0	0	0	0	0	0	2	0	0	135	137
Total	90	96	73	203	57	91	76	48	143	142	89.7939

2

3 15

Truth

	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74	0	0	0	0	0	0	0	0	0	74
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	0	0	49	0	0	0	0	0	12	9	70
Forest	3	0	0	203	0	0	0	0	0	0	206
Driveway	1	0	0	0	57	0	0	0	2	0	60
Sand	0	0	0	0	0	86	0	0	0	0	86
Circle	0	0	22	0	0	0	59	1	0	5	87
NoName	12	0	1	0	0	0	17	46	0	0	76
Sc/Bush	0	0	1	0	0	5	0	1	129	0	136
Sc/Weed	0	0	0	0	0	0	0	0	0	123	123

3 12

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74	0	0	0	0	0	0	0	0	0	74
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	0	0	71	0	1	0	0	0	0	0	72
Forest	0	0	0	203	0	0	0	0	0	2	205
Driveway	0	0	1	0	56	0	0	0	0	0	57
Sand	0	0	0	0	0	86	0	0	0	0	86
Circle	0	0	0	0	0	0	65	0	0	2	67
NoName	0	0	0	0	0	0	10	48	0	0	58
Sc/Bush	16	0	1	0	0	5	0	0	143	4	169
Sc/Weed	0	0	0	0	0	0	1	0	0	129	130
Total	90	96	73	203	57	91	76	48	143	137	95.2894 3

1 9

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	79	0	0	0	0	0	0	0	0	0	79
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	2	0	72	0	6	0	0	0	0	0	80
Forest	0	0	0	203	0	0	0	0	0	0	203
Driveway	0	0	1	0	51	0	0	0	0	0	52
Sand	0	0	0	0	0	88	0	0	0	0	88
Circle	0	0	0	0	0	0	64	0	1	0	65
NoName	0	0	0	0	0	0	1	29	33	0	63
Sc/Bush	8	0	0	0	0	3	9	19	109	137	285
Sc/Weed	1	0	0	0	0	0	2	0	0	136	139
Total	90	96	73	203	57	91	76	48	143	273	90.9715 2

4 7

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	77	0	0	0	0	0	0	0	0	0	77
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	0	0	50	0	10	0	0	0	0	0	60
Forest	0	0	0	203	0	0	0	0	0	1	204
Driveway	0	0	23	0	47	0	0	0	0	0	70
Sand	1	0	0	0	0	84	0	0	0	0	85
Circle	0	0	0	0	0	0	57	0	0	0	57
NoName	0	0	0	0	0	7	19	48	0	0	74
Sc/Bush	12	0	0	0	0	0	0	0	143	0	155
Sc/Weed	0	0	0	0	0	0	0	0	0	136	136
Total	90	96	73	203	57	91	76	48	143	137	92.3454 3

presc/tg (1 3)

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74	0	0	0	0	0	0	0	0	0	74
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	0	0	73	0	7	0	0	0	0	0	80
Forest	0	0	0	203	0	0	0	0	0	1	204
Driveway	0	0	0	0	50	0	0	0	0	0	50
Sand	14	0	0	0	0	91	0	0	0	0	105
Circle	0	0	0	0	0	0	65	0	8	7	80
NoName	2	0	0	0	0	0	6	45	47	0	100
Sc/Bush	0	0	0	0	0	0	5	3	88	0	96

presc/cla s2 (14 15)

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	62	7	0	0	0	0	13	9	7	0	98
Roof	0	31	0	0	0	2	1	2	4	2	42
Road	0	0	30	0	8	0	1	0	10	21	70
Forest	0	0	0	203	0	0	0	0	0	0	203
Driveway	0	0	18	0	44	0	0	0	0	70	132
Sand	0	6	0	0	0	84	0	0	0	0	90
Circle	4	12	21	0	0	0	25	0	27	1	90
NoName	18	27	0	0	0	5	8	24	10	0	92
Sc/Bush	6	13	2	0	0	0	28	13	83	1	146
Sc/Weed	0	0	2	0	5	0	0	0	2	42	51
Total	90	96	73	203	57	91	76	48	143	137	61.6290 1

4	7 Truth Parking	St_conf Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	2	0	0	0	0	0	0	0	0	0	2
Roof	0	0	0	0	0	0	0	0	0	0	0
Road	1	0	0	0	0	0	0	0	0	0	1
Forest	0	0	0	32	0	0	0	0	2	5	39
Driveway	1	0	0	0	2	0	0	0	1	0	4
Sand	1	0	0	0	0	4	0	0	3	0	8
Circle	0	0	0	0	0	0	0	0	0	0	0
NoName	0	0	0	0	0	0	0	0	0	0	0
Sc/Bush	2	0	0	0	1	0	0	0	18	2	23
Sc/Weed	0	0	0	6	0	0	0	0	4	13	23
Total	7	0	0	38	3	4	0	0	28	20	71

1	3 Truth Parking	St_conf Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	2	0	0	0	0	0	0	0	0	0	2
Roof	0	0	0	0	0	0	0	0	0	0	0
Road	0	0	2	1	0	0	0	0	0	1	4
Forest	0	0	0	30	0	0	0	0	0	0	30
Driveway	0	0	0	0	1	0	0	0	0	0	1
Sand	0	0	0	0	0	8	0	0	2	0	10
Circle	0	0	0	0	0	0	1	0	3	3	7
NoName	0	0	0	0	0	0	0	1	10	3	14
Sc/Bush	0	0	0	0	0	0	0	0	7	2	9
Sc/Weed	0	0	0	8	0	0	0	1	11	3	23

Mean:	87.58
Std:	9.94
Mean +1/2 std:	92.55
Mean - ½ std:	82.61

Table A-3: Tank Scene 2-Band - SCR/LOG Stimuli/Response Matrices

bands	1	9	3	9	3	15	1	3	3	12	4	7	14	15	9	12
threshold	0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25	
ROC	61	6	19	48	67	0	66	1	7	60	67	0	0	67	52	15
	0	111	0	111	30	81	0	111	0	111	12	99	0	111	0	111
	0.5		0.5		0.5		0.5		0.5		0.5		0.5		0.5	
	0	67	0	67	7	60	0	67	0	67	62	5	0	67	0	67
	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111
	0.05		0.05		0.05		0.05		0.05		0.05		0.05		0.05	
	67	0	67	0	67	0	67	0	67	0	67	0	4	63	67	0
	91	20	87	24	99	12	47	64	71	40	77	34	0	111	87	24
	0.05		0.05		0.05											
	67	0	67	0	67	0										
	0	111	0	111	0	111										
	0.25		0.25		0.25											
	66	1	67	0	67	0										
	0	111	0	111	0	111										
	0.75		0.75		0.75		0.75		0.75		0.75		0.75		0.75	
	167	8	175	0	175	0	66	1	67	0	66	1	40	135	62	5
	0	539	539	0	539	0	0	111	0	111	0	111	20	519	0	111
Pt=0.075																
	67	0	67	0	67	0										
	0	111	0	111	0	111										
													0.15		0.15	
Pt=0.15																
	167	8	175	0	175	0	67	0	67	0	66	1	169	6	66	1
	0	539	539	0	539	0	0	111	0	111	0	111	236	303	11	100
Pt=0.1													0.1		0.1	
	67	0	175	0	175	0	67	0	67	0	67	0	173	2	66	1
	0	111	539	0	539	0	0	111	0	111	0	111	262	277	13	98

Table A- 4: Tank Scene 2-Band SCR Analysis

Bands	1 9			3 9			3 15			1 3			3 12			4 7			14 15			9 12			4 7 st_cont			1 3 st_conf		
	Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
SCR																														
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00			0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00
	0.91	0.00	0.91	0.28	0.00	0.28	0.10	0.00	0.10	0.99	0.00	0.99	0.10	0.00	0.10	0.93	0.00	0.93	0.00	0.00	0.00	0.78	0.00	0.78	1.00	0.07	0.93	0.00	0.00	0.00
	1.00	0.82	0.18	1.00	0.78	0.22	1.00	0.27	0.73	1.00	0.42	0.58	1.00	0.64	0.36	1.00	0.11	0.89	0.06	0.00	0.06	1.00	0.78	0.22	0.50	0.00	0.50	0.00	0.00	0.00
	1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.89	0.11	1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.69	0.31	1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.59	0.41	0.00	0.23	-0.23
			0.00			0.00	1.00	1.00	0.00			0.00			0.00	1.00	1.00	0.00			0.00			0.00			0.00			0.00
Summed Difference			1.09			0.50			0.94			1.56			0.46			2.12			0.06			0.99			1.85			-0.23
RANK			3.00			1.00			1.00			3.00			3.00			3.00			2.00			2.00						

Table A-5: Tank Scene 2-Band LOG Analysis

Bands	1 9			3 9			3 15			1 3			3 12			4 7			14 15			9 12		
	Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.95	0.00	0.95	1.00	1.00	0.00	1.00	1.00	0.00	0.99	0.00	0.99	1.00	0.00	1.00	0.99	0.00	0.99	0.23	0.04	0.19	0.09	0.12	-0.03
	0.95	0.00	0.95	1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	1.00	0.99	0.00	0.99	0.97	0.44	0.53	0.93	0.00	0.93
	1.00	0.00	1.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.99	0.49	0.50	0.99	0.10	0.89
	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
			2.91			0.00			0.00			2.99			3.00			2.97			1.22			1.78
RANK			3.00			1.00			1.00			3.00			3.00			3.00			2.00			2.00

Table A-6: Tank Scene 4-Band Results

Image Name		TANK-4 band		
		1	8	5
p1/clas1		tdiv orig/p1/clas1	tdiv mod/p1/clas1	fsbs/p1/clas1
1	9			
3	12	1	1	3
4	14	4	3	6
7	15	12	7	9
		14	12	12
		9		
		tdiv orig/p1/clas2	tdiv mod/p1/clas2	fsbs/p1/clas2
		1	1	3
		7	3	7
		9	7	9
		14	12	14
		10	12	
p2/clas2		tdiv orig/p2/clas2	tdiv mod/p2/clas2	fsbs/p2/clas2
1	9	1	1	3
3	13	6	3	6
4	14	9	6	9
6	15	14	13	12
		13	14	15
		tdiv orig/p2/tg	tdiv mod/p2/tg	fsbs/p2/tg
		4	1	1
		6	3	3
		9	4	4
		13	15	6
				7
		tdiv orig/p1/tg	tdiv/p1/tg	fsbs/p1/tg
		4	1	1
		7	3	3
		9	4	4
		12	15	7
		16	17	
		sbf_int/p1	sbf_int/full	
		3	3	
		9	9	
		14	11	
		15	15	
			19	3
		presc/clas1	presc/tg	tdiv orig/full/clas1
		3	1	2
		9	3	4
		14	7	14
		15	9	15

Table A-7: Tank Scene 4-Band GML Confusion Matrices

1

	Truth										
	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	76	0	0	0	0	0	0	0	0	0	76
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	0	0	71	0	0	0	0	0	0	0	71
Forest	0	0	0	203	0	0	0	0	0	0	203
Driveway	0	0	2	0	57	0	0	0	0	0	59
Sand	9	0	0	0	0	91	0	0	0	0	100
Circle	0	0	0	0	0	0	69	0	0	0	69
NoName	0	0	0	0	0	0	7	48	0	0	55
Sc/Bush	5	0	0	0	0	0	0	0	143	0	148
Sc/Weed	0	0	0	0	0	0	0	0	0	137	137
Total	90	96	73	203	57	91	76	48	143	137	97.25
											3

2

	Truth										
	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74	0	0	0	0	0	0	0	0	0	74
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	0	0	73	0	0	0	0	0	0	0	73
Forest	0	0	0	203	0	0	0	0	0	0	203
Driveway	0	0	0	0	57	0	0	0	0	0	57
Sand	6	0	0	0	0	90	0	0	0	0	96
Circle	0	0	0	0	0	0	58	2	0	0	60
NoName	0	0	0	0	0	0	18	46	0	0	64
Sc/Bush	10	0	0	0	0	1	0	0	143	0	154
Sc/Weed	0	0	0	0	0	0	0	0	0	137	137
Total	90	96	73	203	57	91	76	48	143	137	95.87
											1

3

	Truth										
	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74	0	0	0	0	0	0	0	0	0	74
Roof	0	96	0	0	0	0	0	0	0	0	96
Road	0	0	71	0	0	0	0	0	0	1	72
Forest	0	0	0	203	0	0	0	0	0	0	203
Driveway	0	0	2	0	57	0	0	0	0	0	59
Sand	13	0	0	0	0	91	0	0	0	0	104
Circle	0	0	0	0	0	0	68	0	0	0	68
NoName	0	0	0	0	0	0	8	48	0	0	56
Sc/Bush	3	0	0	0	0	0	0	0	143	0	146
Sc/Weed	0	0	0	0	0	0	0	0	0	136	136
Total	90	96	73	203	57	91	76	48	143	137	96.86
											2

4

	Truth										
	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	87	0	0	0	0	0	0	0	0	0	87
Roof	3	96	0	0	0	0	0	0	0	0	99
Road	0	0	73	0	2	0	0	0	0	0	75
Forest	0	0	0	203	0	0	0	0	0	0	203
Driveway	0	0	0	0	55	0	0	0	0	0	55
Sand	0	0	0	0	0	82	0	0	0	0	82
Circle	0	0	0	0	0	0	70	3	0	0	73
NoName	0	0	0	0	0	0	6	45	0	0	51
Sc/Bush	0	0	0	0	0	0	0	0	143	0	143
Sc/Weed	0	0	0	0	0	9	0	0	0	137	146

5.00

	Truth										
	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	90.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	90.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	73.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	74.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	0.00	0.00	56.00	0.00	0.00	0.00	0.00	0.00	56.00
Sand	0.00	0.00	0.00	0.00	0.00	89.00	0.00	0.00	0.00	0.00	89.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	72.00	0.00	0.00	0.00	72.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	4.00	48.00	0.00	0.00	52.00
Sc/Bush	0.00	0.00	0.00	0.00	0.00	2.00	0.00	0.00	143.00	1.00	146.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	136.00	136.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	98.72
											3.00

6.00

	Truth										
	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	90.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	90.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	73.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	73.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	0.00	0.00	57.00	0.00	0.00	0.00	0.00	0.00	57.00
Sand	0.00	0.00	0.00	0.00	0.00	86.00	0.00	0.00	0.00	0.00	86.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	67.00	5.00	0.00	0.00	72.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	9.00	43.00	0.00	0.00	52.00
Sc/Bush	0.00	0.00	0.00	0.00	0.00	5.00	0.00	0.00	143.00	0.00	148.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	137.00	137.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	97.64
											3.00

7.00

	Truth										
	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	74.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	60.00	0.00	8.00	0.00	0.00	0.00	0.00	0.00	68.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	13.00	0.00	49.00	0.00	0.00	0.00	0.00	0.00	62.00
Sand	13.00	0.00	0.00	0.00	0.00	91.00	0.00	0.00	0.00	0.00	104.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	70.00	0.00	0.00	0.00	70.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	6.00	48.00	0.00	0.00	54.00
Sc/Bush	3.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	143.00	0.00	146.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	137.00	137.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	95.29
											1.00

8.00

	Truth										
	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	79.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	79.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	1.00	0.00	73.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	75.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	0.00	0.00	56.00	0.00	0.00	0.00	0.00	0.00	56.00
Sand	7.00	0.00	0.00	0.00	0.00	90.00	0.00	0.00	0.00	0.00	97.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	68.00	0.00	0.00	0.00	68.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	8.00	48.00	0.00	0.00	56.00
Sc/Bush	3.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	143.00	0.00	147.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	137.00	137.00

13.00

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	81.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	81.00
Roof	8.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	104.00
Road	1.00	0.00	73.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	74.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	0.00	0.00	57.00	0.00	0.00	0.00	0.00	0.00	57.00
Sand	0.00	0.00	0.00	0.00	0.00	81.00	0.00	0.00	0.00	0.00	81.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	68.00	2.00	0.00	0.00	70.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	8.00	46.00	0.00	0.00	54.00
Sc/Bush	0.00	0.00	0.00	0.00	0.00	10.00	0.00	0.00	143.00	0.00	153.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	137.00	137.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	96.66
											2.00

14.00

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	74.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	72.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	72.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	1.00	0.00	57.00	0.00	0.00	0.00	0.00	0.00	58.00
Sand	13.00	0.00	0.00	0.00	0.00	91.00	0.00	0.00	0.00	0.00	104.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	63.00	0.00	0.00	0.00	63.00
NoName	1.00	0.00	0.00	0.00	0.00	0.00	13.00	48.00	0.00	0.00	62.00
Sc/Bush	2.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	143.00	0.00	145.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	137.00	137.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	96.57
											2.00

15.00

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	74.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	61.00	0.00	7.00	0.00	0.00	0.00	0.00	0.00	68.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	12.00	0.00	50.00	0.00	0.00	0.00	0.00	0.00	62.00
Sand	12.00	0.00	0.00	0.00	0.00	90.00	0.00	0.00	0.00	0.00	102.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	67.00	0.00	0.00	0.00	67.00
NoName	1.00	0.00	0.00	0.00	0.00	0.00	9.00	48.00	0.00	0.00	58.00
Sc/Bush	3.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	143.00	0.00	147.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	137.00	137.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	95.09
											1.00

16.00

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	86.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	86.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	72.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	72.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	1.00	0.00	57.00	0.00	0.00	0.00	0.00	0.00	58.00
Sand	0.00	0.00	0.00	0.00	0.00	84.00	0.00	0.00	0.00	0.00	84.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	64.00	4.00	0.00	3.00	71.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	10.00	44.00	0.00	0.00	54.00
Sc/Bush	2.00	0.00	0.00	0.00	0.00	7.00	1.00	0.00	143.00	0.00	153.00
Sc/Weed	2.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	134.00	137.00

9.00

Truth

	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	87.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	87.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	73.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	73.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	0.00	0.00	57.00	0.00	0.00	0.00	0.00	0.00	57.00
Sand	0.00	0.00	0.00	0.00	0.00	86.00	0.00	0.00	0.00	0.00	86.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	67.00	3.00	0.00	0.00	70.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	9.00	45.00	0.00	0.00	54.00
Sc/Bush	2.00	0.00	0.00	0.00	0.00	5.00	0.00	0.00	143.00	0.00	150.00
Sc/Weed	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	137.00	138.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	97.55
											3.00

10.00

Truth

	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	82.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	82.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	4.00	0.00	73.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	77.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	0.00	0.00	57.00	0.00	0.00	0.00	0.00	0.00	57.00
Sand	0.00	0.00	0.00	0.00	0.00	88.00	0.00	0.00	0.00	0.00	88.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	67.00	1.00	0.00	0.00	68.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	9.00	47.00	0.00	0.00	56.00
Sc/Bush	4.00	0.00	0.00	0.00	0.00	3.00	0.00	0.00	143.00	0.00	150.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	137.00	137.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	97.45
											3.00

11.00

Truth

	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	74.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	69.00	0.00	0.00	0.00	0.00	0.00	4.00	4.00	77.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	0.00	0.00	57.00	0.00	0.00	0.00	0.00	0.00	57.00
Sand	0.00	0.00	0.00	0.00	0.00	90.00	0.00	0.00	0.00	0.00	90.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	61.00	1.00	0.00	0.00	62.00
NoName	1.00	0.00	0.00	0.00	0.00	0.00	15.00	47.00	0.00	0.00	63.00
Sc/Bush	15.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	139.00	2.00	158.00
Sc/Weed	0.00	0.00	3.00	0.00	0.00	0.00	0.00	0.00	0.00	131.00	134.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	94.90
											1.00

12.00

Truth

	Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	74.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	73.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	74.00
Forest	0.00	0.00	0.00	200.00	0.00	0.00	0.00	0.00	0.00	0.00	200.00
Driveway	0.00	0.00	0.00	0.00	56.00	0.00	0.00	0.00	0.00	0.00	56.00
Sand	9.00	0.00	0.00	0.00	0.00	87.00	0.00	0.00	0.00	0.00	96.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	70.00	0.00	0.00	0.00	70.00
NoName	2.00	0.00	0.00	0.00	0.00	0.00	6.00	48.00	0.00	0.00	56.00
Sc/Bush	5.00	0.00	0.00	0.00	0.00	4.00	0.00	0.00	143.00	1.00	153.00
Sc/Weed	0.00	0.00	0.00	3.00	0.00	0.00	0.00	0.00	0.00	136.00	139.00

17.00

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	86.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	86.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	72.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	73.00
Forest	0.00	0.00	0.00	202.00	0.00	0.00	0.00	0.00	0.00	0.00	202.00
Driveway	0.00	0.00	1.00	0.00	56.00	0.00	0.00	0.00	0.00	0.00	57.00
Sand	0.00	0.00	0.00	0.00	0.00	83.00	0.00	0.00	0.00	0.00	83.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	67.00	0.00	0.00	2.00	69.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	1.00	48.00	0.00	0.00	49.00
Sc/Bush	4.00	0.00	0.00	0.00	0.00	8.00	6.00	0.00	143.00	0.00	161.00
Sc/Weed	0.00	0.00	0.00	1.00	0.00	0.00	2.00	0.00	0.00	135.00	138.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	96.96
											2.00

Mean: 96.57
Std: 1.03
+1/2 std: 97.08
-1/2 std: 96.05

18.00

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	74.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	74.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	0.00	0.00	69.00	0.00	0.00	0.00	0.00	0.00	4.00	4.00	77.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	0.00	0.00	57.00	0.00	0.00	0.00	0.00	0.00	57.00
Sand	0.00	0.00	0.00	0.00	0.00	90.00	0.00	0.00	0.00	0.00	90.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	61.00	1.00	0.00	0.00	62.00
NoName	1.00	0.00	0.00	0.00	0.00	0.00	15.00	47.00	0.00	0.00	63.00
Sc/Bush	15.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	139.00	2.00	158.00
Sc/Weed	0.00	0.00	3.00	0.00	0.00	0.00	0.00	0.00	0.00	131.00	134.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	94.90
											1.00

19.00

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	77.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	77.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	3.00	0.00	73.00	0.00	8.00	0.00	0.00	0.00	0.00	0.00	84.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	0.00	0.00	0.00	0.00	49.00	0.00	0.00	0.00	0.00	0.00	49.00
Sand	2.00	0.00	0.00	0.00	0.00	88.00	0.00	0.00	0.00	0.00	90.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	72.00	2.00	0.00	0.00	74.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	4.00	46.00	0.00	0.00	50.00
Sc/Bush	8.00	0.00	0.00	0.00	0.00	3.00	0.00	0.00	143.00	0.00	154.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	137.00	137.00
Total	90.00	96.00	73.00	203.00	57.00	91.00	76.00	48.00	143.00	137.00	96.57
											2.00

20.00

	Truth Parking	Roof	Road	Forest	Driveway	Sand	Circle	NoName	Sc/Bush	Sc/Weed	Total
Parking	76.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	76.00
Roof	0.00	96.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.00
Road	4.00	0.00	73.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	77.00
Forest	0.00	0.00	0.00	203.00	0.00	0.00	0.00	0.00	0.00	0.00	203.00
Driveway	2.00	0.00	0.00	0.00	57.00	0.00	0.00	0.00	0.00	0.00	59.00
Sand	0.00	0.00	0.00	0.00	0.00	89.00	0.00	0.00	0.00	0.00	89.00
Circle	0.00	0.00	0.00	0.00	0.00	0.00	67.00	2.00	0.00	0.00	69.00
NoName	0.00	0.00	0.00	0.00	0.00	0.00	9.00	46.00	0.00	0.00	55.00
Sc/Bush	8.00	0.00	0.00	0.00	0.00	2.00	0.00	0.00	143.00	1.00	154.00
Sc/Weed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	136.00	136.00

Table A-8: Tank Scene 4-Band SCR/LOG Stimuli/Response Matrices

Band set		1		2		3		4		5		6		7		8		9		10	
threshold	SCR 0.25																				
ROC		0	67	0	67	0	67	14	53	16	51	0	67	0	67	13	54	0	67	0	67
		0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111
	0.1																				
		10	57	1	66	1	66	64	3	65	2	22	45	66	1	66	1	58	9	63	4
		12	99	0	111	0	111	0	111	0	111	30	81	0	111	0	111	31	80	28	83
	0.05																				
		67	0	4	63	4	63	67	0	67	0	67	0	66	0	66	1	67	0	67	0
		75	36	0	111	0	111	63	48	60	51	104	7	0	111	1	110	105	6	102	9
	Log 0.05																				
		65	2	65	2	66	1	67	0	67	0	67	0	67	0	67	0	67	0	67	0
		0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111
	0.15																				
		65	2	64	3	65	2	67	0	67	0	67	0	67	0	67	0	67	0	67	0
		0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111
		11		12		13		14		15		16		17		18		19		20	
SCR	0.25																				
		0	67	67	0	64	3	66	1	0	67	0	67	0	67	0	67	64	3	0	67
		0	111	111	0	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111
	0.1																				
		1	66	66	1	67	0	66	1	17	50	4	63	54	13	1	66	66	1	54	13
		0	111	0	111	41	70	7	104	0	111	0	111	0	111	0	111	0	111	29	82
	0.05																				
		4	63	67	0	67	0	67	0	57	10	5	62	67	0	4	63	67	0	67	0
		0	111	10	101	85	26	58	53	0	111	0	111	56	55	0	111	25	86	102	9
Log	0.05																				
		65	2	67	0	66	1	67	0	67	0	67	0	66	1	65	2	67	0	67	0
		0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111
	0.15																				
		65	2	67	0	66	1	67	0	67	0	67	0	66	1	65	2	67	0	67	0
		0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111	0	111

Table A-9: Tank Scene 4-Band SCR Analysis

	1.00			2.00			3.00			4.00			5.00		
Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	
	0.00	0.00	0.00	0.00	0.00	0.00 same as 2				0.00	0.00	0.00	0.00	0.00	0.00
	0.15	0.11	0.04	0.01	0.00	0.01				0.21	0.00	0.21	0.24	0.00	0.24
	1.00	0.68	0.32	0.06	0.00	0.06				0.96	0.00	0.96	0.97	0.00	0.97
	1.00	1.00	0.00	1.00	1.00	0.00				1.00	0.57	0.43	1.00	0.54	0.46
			0.37			0.07				1.00	1.00		1.00	1.00	
			1.00			1.00						1.60			1.67
												3.00			3.00
	6.00			7.00			8.00			9.00			10.00		
Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.33	0.27	0.06	0.99	0.00	0.99	0.19	0.00	0.19	0.87	0.28	0.59	0.94	0.25	0.69
	1.00	0.94	0.06	0.99	0.00	0.99	0.99	0.00	0.99	1.00	0.95	0.05	1.00	0.92	0.08
	1.00	1.00	0.00	1.00	1.00	0.00	0.99	0.01	0.98	1.00	1.00	0.00	1.00	1.00	0.00
			0.12			1.97	1.00	1.00				0.64			0.77
									2.16						
			2.00			3.00			3.00			2.00			2.00
	11.00			12.00			13.00			14.00			15.00		
Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	
same as 2				0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
				0.99	0.00	0.99	0.96	0.00	0.96	0.99	0.00	0.99	0.25	0.00	0.25
				1.00	0.09	0.91	1.00	0.37	0.63	0.99	0.06	0.92	0.85	0.00	0.85
				1.00	1.00	0.00	1.00	0.77	0.23	1.00	0.52	0.48	1.00	1.00	0.00
						1.89	1.00	1.00		1.00	1.00				1.10
									1.82			2.38			
						3.00			3.00			3.00			2.00
	16.00			17.00			18.00			19.00			20.00		
Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	Hit		False Alarm	
	0.00	0.00	0.00	0.00	0.00	0.00 same as 2				0.00	0.00	0.00	0.00	0.00	0.00
	0.06	0.00	0.06	0.81	0.00	0.81				0.96	0.00	0.96	0.81	0.26	0.54
	0.07	0.00	0.07	1.00	0.50	0.50				0.99	0.00	0.99	1.00	0.92	0.08
	1.00	1.00	0.00	1.00	1.00	0.00				1.00	0.23	0.77	1.00	1.00	0.00
			0.13			1.30				1.00	1.00				0.63
												2.72			
			1.00			2.00						3.00			1.00

Mean:	1.07
Std:	0.89
Mean + ½ std:	1.52
Mean - ½ std:	0.63

Table A-10: Desert Scene 2-Band Results

p1=p2	tdiv orig/p1/clas2	fsbs/p1/clas2	tdiv mod/clas2	tdiv orig/tg
				1
1	3	7	3	10
3	7	10	7	
7				
9				
10				
	tdiv orig/p1/clas1	fsbs/p1/clas1	tdiv mod/clas1	fsbs/tg
				1
	3	7	3	10
	7	10	7	
	presc/clas2	presc/tg	sbf - interval	
	3	3		
	7	7	3	
			9	

Table A-11: Desert Scene 2-Band Gaussian Maximum Likelihood Confusion Matrices

3 7

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350.00	0.00	0.00	0.00	2.00	0.00	3.00	0.00	355.00
sand	0.00	113.00	0.00	0.00	0.00	0.00	0.00	0.00	113.00
vegetation	0.00	0.00	42.00	0.00	11.00	0.00	0.00	0.00	53.00
shadow	0.00	0.00	0.00	73.00	0.00	0.00	0.00	0.00	73.00
camo	0.00	0.00	10.00	0.00	21.00	0.00	0.00	16.00	47.00
des pav1	0.00	0.00	0.00	0.00	0.00	365.00	0.00	1.00	366.00
des pav2	0.00	0.00	0.00	0.00	0.00	0.00	233.00	40.00	273.00
des pav3	0.00	0.00	0.00	0.00	0.00	14.00	137.00	159.00	310.00
total	350.00	113.00	52.00	73.00	34.00	379.00	373.00	216.00	86.28
RANK									2.00

7 10

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	286.00	0.00	17.00	1.00	1.00	0.00	0.00	0.00	305.00
sand	0.00	113.00	0.00	0.00	0.00	0.00	0.00	0.00	113.00
vegetation	4.00	0.00	27.00	0.00	0.00	0.00	0.00	0.00	31.00
shadow	0.00	0.00	0.00	72.00	0.00	0.00	0.00	0.00	72.00
camo	60.00	0.00	7.00	0.00	33.00	0.00	6.00	0.00	106.00
des pav1	0.00	0.00	1.00	0.00	0.00	375.00	0.00	0.00	376.00
des pav2	0.00	0.00	0.00	0.00	0.00	0.00	322.00	1.00	323.00
des pav3	0.00	0.00	0.00	0.00	0.00	4.00	45.00	215.00	264.00
total	350.00	113.00	52.00	73.00	34.00	379.00	373.00	216.00	90.75
									3.00

Mean:	85.66
Std:	3.97
Mean + ½ std:	87.64
Mean - ½ std:	83.68

1 10

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	351.00
sand	0.00	113.00	0.00	0.00	0.00	0.00	0.00	0.00	113.00
vegetation	0.00	0.00	37.00	13.00	0.00	0.00	0.00	0.00	50.00
shadow	0.00	0.00	4.00	60.00	0.00	0.00	0.00	0.00	64.00
camo	0.00	0.00	9.00	0.00	1.00	22.00	10.00	0.00	42.00
des pav1	0.00	0.00	1.00	0.00	4.00	348.00	27.00	0.00	380.00
des pav2	0.00	0.00	0.00	0.00	20.00	7.00	165.00	1.00	193.00
des pav3	0.00	0.00	0.00	0.00	9.00	2.00	171.00	215.00	397.00
total	350.00	113.00	52.00	73.00	34.00	379.00	373.00	216.00	81.07
									1.00

3 9

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	350.00
sand	0.00	113.00	0.00	0.00	0.00	0.00	0.00	0.00	113.00
vegetation	0.00	0.00	30.00	5.00	0.00	41.00	11.00	0.00	87.00
shadow	0.00	0.00	2.00	68.00	0.00	0.00	0.00	0.00	70.00
camo	0.00	0.00	2.00	0.00	30.00	9.00	1.00	14.00	56.00
des pav1	0.00	0.00	12.00	0.00	0.00	328.00	0.00	0.00	340.00
des pav2	0.00	0.00	5.00	0.00	0.00	0.00	265.00	26.00	296.00
des pav3	0.00	0.00	1.00	0.00	4.00	1.00	96.00	176.00	278.00
total	350.00	113.00	52.00	73.00	34.00	379.00	373.00	216.00	85.53
									2.00

st_conf 3 7

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	
tent	1.00	8.00	0.00	0.00	0.00	0.00	4.00	1.00	14.00
sand	1.00	2.00	0.00	1.00	0.00	0.00	0.00	0.00	4.00
vegetation	0.00	0.00	3.00	0.00	0.00	0.00	0.00	0.00	3.00
shadow	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
camo	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	1.00
des pav1	1.00	0.00	0.00	0.00	0.00	29.00	0.00	1.00	31.00
des pav2	2.00	0.00	0.00	0.00	1.00	3.00	17.00	3.00	26.00
des pav3	3.00	0.00	0.00	1.00	0.00	2.00	13.00	7.00	26.00
total	8.00	10.00	4.00	2.00	1.00	34.00	34.00	12.00	56.19

st_conf 1 10

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
sand	0.00	2.00	0.00	0.00	0.00	0.00	0.00	1.00	3.00
vegetation	0.00	0.00	4.00	0.00	0.00	0.00	1.00	0.00	5.00
shadow	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
camo	0.00	0.00	2.00	2.00	1.00	4.00	4.00	0.00	13.00
des pav1	0.00	0.00	0.00	1.00	0.00	19.00	2.00	0.00	22.00
des pav2	0.00	1.00	2.00	0.00	0.00	1.00	13.00	2.00	19.00
des pav3	3.00	0.00	3.00	0.00	0.00	0.00	9.00	25.00	40.00

Table A-12: Desert Scene 2-Band SCR/LOG Stimuli/Response Matrices

3	7	7	10	1	10	3	9
0.25		0.25		0.25			
138	4	138	4	28	114	133	9
84	272	76	280	0	356	92	264
0.15		0.15		0.15			
142	0	140	2	125	17	140	2
139	217	189	167	0	356	285	71
0.5		0.5		0.5			
26	116	1	141	7	135	20	122
2	354	25	331	0	356	10	346
0.05		0.05		0.05			
142	0	136	6	142	0	142	0
298	58	65	291	54	302	50	306
0.1		0.1		0.1			
142	0	136	6	142	0	142	0
285	71	65	291	53	303	36	320
0.25		0.25		0.25			
138	4	134	8	142	0	142	0
53	303	59	297	0	356	13	343

Table A-13: Desert Scene 2-Band SCR Analysis

	3 7 Hit	False Alarm		7 10 Hit	False Alarm		1 10 Hit	False Alarm		3 9 Hit	False Alarm		3 7 Hit	st_conf False Alarm		1 10 Hit	st_conf False Alarm	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.18	0.01	0.18	0.01	0.07	-0.06	0.05	0.00	0.05	0.14	0.03	0.11	0.00	0.07	-0.07	0.00	0.00	0.00
	0.97	0.24	0.74	0.97	0.21	0.76	0.20	0.00	0.20	0.94	0.26	0.68	0.00	0.40	-0.40	1.00	0.00	1.00
	1.00	0.39	0.61	0.99	0.53	0.46	0.88	0.00	0.88	0.99	0.80	0.19	0.00	0.00	0.00	0.00	0.00	0.00
	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
			1.52			1.15			1.13			0.98			-0.47			1.00
RANK			3			2			2			1						

Mean:	1.19
Std:	0.23
Mean + ½ std:	1.31
Mean - ½ std:	1.08

Table A-14: Desert Scene 2-Band LOG Analysis

3 7 Hit	False Alarm		7 10 Hit	False Alarm		1 10 Hit	False Alarm		3 9 Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.97	0.15	0.82	0.94	0.17	0.78	1.00	0.00	1.00	1.00	0.04	0.96
1.00	0.80	0.20	0.96	0.18	0.78	1.00	0.15	0.85	1.00	0.10	0.90
1.00	0.84	0.16	0.96	0.18	0.78	1.00	0.15	0.85	1.00	0.14	0.85
1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
		1.19			2.33			2.70			2.72
		1			2			3			3

Mean:	2.23
Std:	0.72
Mean + ½ std:	2.59
Mean - ½ std:	1.87

Table A-15: Desert Scene 4-Band Results

		1	3	4
p1/clas1		tdiv orig/p1/clas1	tdiv mod/p1/clas1	fsbs/p1/clas1
1	7			
2	8	3	3	2
3	9	5	5	5
5	10	8	7	7
		10	8	10
			10	11
		tdiv orig/p1/clas2	tdiv mod/p1/clas2	fsbs/p1/clas2
p1=p2				
		3	3	3
		5	5	5
		8	7	7
		10	9	10
		6	12	7
		tdiv orig/p1/tg	tdiv mod/p1/tg	fsbs/p1/tg
		1	2	1
		3	5	7
		7	9	8
		10	10	10
			8	14
		sbf_int/p1	fsbs/full/clas1	sbf_int/full
		1	4	3
		3	7	4
		7	8	7
		9	10	9
		13		
		presc/clas1	presc/tg	
		1	1	
		3	3	
		7	7	
		9	10	

Table A-16: Desert Scene 4-Band Gaussian Maximum Likelihood Confusion Matrices

1

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350	0	0	0	0	0	0	0	350
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	49	0	0	0	0	0	49
shadow	0	0	0	73	0	0	0	0	73
camo	0	0	3	0	34	0	2	4	43
des pav1	0	0	0	0	0	377	0	0	377
des pav2	0	0	0	0	0	0	360	0	360
des pav3	0	0	0	0	0	2	11	212	225
total	350	113	52	73	34	379	373	216	98.62
RANK									3

2

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350	0	0	0	0	0	0	0	350
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	42	4	0	0	0	0	46
shadow	0	0	3	69	0	0	0	0	72
camo	0	0	7	0	34	3	16	3	63
des pav1	0	0	0	0	0	373	0	0	373
des pav2	0	0	0	0	0	0	325	0	325
des pav3	0	0	0	0	0	3	32	213	248
total	350	113	52	73	34	379	373	216	95.53
									2

3

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	348	0	0	0	0	0	0	0	348
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	47	0	0	0	0	0	47
shadow	0	0	0	73	0	0	0	0	73
camo	2	0	5	0	34	0	2	5	48
des pav1	0	0	0	0	0	379	0	0	379
des pav2	0	0	0	0	0	0	365	0	365
des pav3	0	0	0	0	0	0	6	211	217
total	350	113	52	73	34	379	373	216	98.74
									3

4

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350	0	0	2	0	0	0	0	352
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	49	0	0	0	0	0	49
shadow	0	0	0	71	0	0	0	0	71
camo	0	0	3	0	34	0	3	3	43
des pav1	0	0	0	0	0	377	0	0	377
des pav2	0	0	0	0	0	0	336	1	337
des pav3	0	0	0	0	0	2	34	212	248
total	350	113	52	73	34	379	373	216	96.98
									2

5

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350	0	0	0	0	0	0	0	350
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	45	0	0	0	0	0	45
shadow	0	0	0	73	0	0	0	0	73
camo	0	0	7	0	34	0	3	5	49
des pav1	0	0	0	0	0	375	0	0	375
des pav2	0	0	0	0	0	0	311	0	311
des pav3	0	0	0	0	0	4	59	211	274
total	350	113	52	73	34	379	373	216	95.09
									2

6

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350	0	0	0	0	0	0	0	350
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	46	0	0	0	0	0	46
shadow	0	0	0	73	0	0	0	0	73
camo	0	0	6	0	34	0	0	4	44
des pav1	0	0	0	0	0	377	0	0	377
des pav2	0	0	0	0	0	1	339	0	340
des pav3	0	0	0	0	0	1	34	212	247
total	350	113	52	73	34	379	373	216	97.11
									2

7

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	349	0	0	1	0	0	0	0	350
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	43	1	0	0	0	0	44
shadow	0	0	0	71	0	0	0	0	71
camo	1	0	9	0	34	0	10	1	55
des pav1	0	0	0	0	0	377	0	0	377
des pav2	0	0	0	0	0	0	359	0	359
des pav3	0	0	0	0	0	2	4	215	221
total	350	113	52	73	34	379	373	216	98.18
									3

8

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	348	0	0	1	0	0	0	0	349
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	46	1	0	0	0	0	47
shadow	0	0	0	71	0	0	0	0	71
camo	2	0	6	0	34	0	0	1	43
des pav1	0	0	0	0	0	378	0	0	378
des pav2	0	0	0	0	0	1	369	0	370
des pav3	0	0	0	0	0	0	4	215	219
total	350	113	52	73	34	379	373	216	98.99
									3

9

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	349	0	0	0	0	0	0	0	349
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	43	2	0	0	0	0	45
shadow	0	0	0	71	0	0	0	0	71
camo	1	0	9	0	34	0	0	1	45
des pav1	0	0	0	0	0	377	0	0	377
des pav2	0	0	0	0	0	1	364	0	365
des pav3	0	0	0	0	0	1	9	215	225
total	350	113	52	73	34	379	373	216	98.49
									3

10

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	346	0	0	0	0	0	0	0	346
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	47	1	0	0	0	0	48
shadow	0	0	0	72	0	0	0	0	72
camo	4	0	5	0	34	0	2	7	52
des pav1	0	0	0	0	0	367	0	1	368
des pav2	0	0	0	0	0	0	311	12	323
des pav3	0	0	0	0	0	12	60	196	268
total	350	113	52	73	34	379	373	216	93.46
									1

11

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350	0	0	1	0	0	0	0	351
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	46	0	0	0	0	0	46
shadow	0	0	0	72	0	0	0	0	72
camo	0	0	6	0	34	0	3	4	47
des pav1	0	0	0	0	0	374	0	0	374
des pav2	0	0	0	0	0	0	318	1	319
des pav3	0	0	0	0	0	5	52	211	268
total	350	113	52	73	34	379	373	216	95.47
									2

12

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350	0	0	0	0	0	0	0	350
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	48	6	0	0	0	0	54
shadow	0	0	0	67	0	0	0	0	67
camo	0	0	4	0	34	6	19	4	67
des pav1	0	0	0	0	0	370	0	0	370
des pav2	0	0	0	0	0	0	321	2	323
des pav3	0	0	0	0	0	3	33	210	246
total	350	113	52	73	34	379	373	216	95.16
									2

13

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350	0	0	0	0	0	0	0	350
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	43	0	0	0	0	0	43
shadow	0	0	0	73	0	0	0	0	73
camo	0	0	9	0	34	0	2	10	55
des pav1	0	0	0	0	0	361	0	0	361
des pav2	0	0	0	0	0	0	281	10	291
des pav3	0	0	0	0	0	18	90	196	304
total	350	113	52	73	34	379	373	216	91.26
									1

14

	tent	sand	vegetation	shadow	camo	des pave1	des pav2	despav3	total
tent	350	0	0	0	0	0	0	0	350
sand	0	113	0	0	0	0	0	0	113
vegetation	0	0	44	0	0	0	0	0	44
shadow	0	0	0	73	0	0	0	0	73
camo	0	0	8	0	34	0	0	4	46
des pav1	0	0	0	0	0	363	0	2	365
des pav2	0	0	0	0	0	0	299	14	313
des pav3	0	0	0	0	0	16	74	196	286
total	350	113	52	73	34	379	373	216	92.59
									1

Mean:	96.12
Std:	2.46
Mean + ½ std:	97.35
Mean - ½ std:	94.87

Table A-17: Desert Scene 4-Band SCR/LOG Stimuli/Response Matrices

Band Set		1		2		3		4		5		6		7	
SCR															
Threshold	0.25	25	117	20	122	28	114	48	94	20	122	136	6	38	104
ROC		0	356	0	356	0	256	0	356	0	356	80	276	0	356
	0.15	131	11	107	35	139	3	136	6	114	28	130	12	123	19
		0	356	0	356	0	356	0	356	0	356	98	258	1	355
	0.5	17	125	0	142	17	125	15	127	0	142	19	123	10	132
		0	356	0	356	0	356	0	356	0	356	0	356	0	356
LOG															
	0.05	141	1	142	0	138	4	142	0	139	3	141	1	138	4
		19	337	48	308	9	347	14	342	23	333	21	335	8	348
	0.15	141	1	142	0	138	4								
		13	343	34	322	5	351								
		8		9		10		11		12		13		14	
		26	116	50	92	28	114	21	121	54	88	17	125	19	123
		3	353	70	286	0	356	0	356	0	356	0	356	0	356
		37	105	39	103	136	6	142	0	137	5	72	70	30	112
		123	233	214	142	0	356	356	0	0	356	1	355	0	356
		0	142	3	139	17	125	17	125	15	127	0	142	7	135
		0	356	0	356	0	356	0	356	0	356	0	356	0	356
		137	5	137	5	142	0	139	3	142	0	142	0	142	0
		7	349	4	352	9	347	18	338	31	325	15	341	5	351

Table A-18: Desert Scene 4-Band SCR Analysis

1.00			2.00			3.00			4.00			5.00			6.00			7.00		
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.12	0.00	0.12	0.14	0.00	0.14	0.12	0.00	0.12	0.11	0.00	0.11	0.14	0.00	0.14	0.13	0.00	0.13	0.07	0.00	0.07
0.18	0.00	0.18	0.75	0.00	0.75	0.20	0.00	0.20	0.34	0.00	0.34	0.80	0.00	0.80	0.96	0.22	0.73	0.27	0.00	0.27
0.92	0.00	0.92	1.00	1.00	0.00	0.98	0.00	0.98	0.96	0.00	0.96	1.00	1.00	0.00	1.00	1.00	0.00	0.87	0.00	0.87
1.00	1.00	0.00			0.00	1.00	1.00	0.00	1.00	1.00	0.00			0.00			0.00	1.00	1.00	0.00
		1.22			0.89			1.30			1.40			0.94			0.87			1.20
		3.00			2.00			3.00			3.00			2.00			2.00			3.00

8.00			9.00			10.00			11.00			12.00			13.00			14.00		
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.18	0.01	0.17	0.02	0.00	0.02	0.12	0.00	0.12	0.12	0.00	0.12	0.11	0.00	0.11	0.12	0.00	0.12	0.05	0.00	0.05
0.26	0.35	-0.08	0.35	0.20	0.16	0.20	0.00	0.20	0.15	0.00	0.15	0.38	0.00	0.38	0.51	0.00	0.50	0.13	0.00	0.13
1.00	1.00	0.00	0.27	0.60	-0.33	0.96	0.00	0.96	1.00	1.00	0.00	0.96	0.00	0.96	1.00	1.00	0.00	0.21	0.00	0.21
		0.00	1.00	1.00	0.00	1.00	1.00	0.00			0.00	1.00	1.00	0.00			0.00	1.00	1.00	0.00
		0.09			-0.15			1.27			0.27			1.45			0.62			0.39
		1.00			1.00			3.00			1.00			3.00			2.00			1.00

Mean:	0.84
Std:	0.52
Mean + ½ std:	1.10
Mean - ½ std:	0.58

Table A-19: Panel Scene 2-Band Results

p1/clas1	
1	46
3	54
7	63
42	64
45	119

p2/clas2	
1	46
2	54
3	60
4	62
42	64

tdiv orig/p1/clas1	tdiv mod/p1/clas1	fsbs/p1/clas1
1	64	42
119	119	119
tdiv orig/p1/clas2	**tdiv mod/p1/clas2**	**fsbs/p1/clas2**
54	64	42
63	119	119
tdiv orig/p2/clas2	**tdiv mod/p2/clas2**	**fsbs/p2/clas2**
42	54	42
54	60	54
tdiv orig/p2/tg	**tdiv mod/p2/tg**	**fsbs/p2/tg**
4	62	4
42	64	42
tdiv orig/p1/tg	**tdiv/p1/tg**	**fsbs/p1/tg**
63	63	7
64	64	42
sbf_int/p1	**sbf_int/p2**	
63	60	
64	64	
presc/clas1	**presc/tg**	**presc/clas2**
42	54	42
64	64	64

Table A-20: Panel Scene 2-Band Gaussian Maximum Likelihood Confusion Matrices

42 119

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	84	0	0	0	28	0	112
Manmade Structures	0	0	57	1	0	0	0	58
Dirt Road	0	0	0	35	0	0	0	35
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	89	0	0	0	122	39	250
Soggy Pasture	0	15	0	0	0	57	162	234
Total	53	188	57	36	32	207	201	70.41
RANK								2

1 119

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	2	0	0	0	0	55
Wheat	0	101	0	0	0	25	21	147
Manmade Structures	0	0	55	0	0	0	0	55
Dirt Road	0	0	0	35	0	0	3	38
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	64	0	0	0	125	36	225
Soggy Pasture	0	23	0	1	0	57	141	222
Total	53	188	57	36	32	207	201	70.03
								2

42 119

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	84	0	0	0	28	0	112
Manmade Structures	0	0	57	1	0	0	0	58
Dirt Road	0	0	0	35	0	0	0	35
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	89	0	0	0	122	39	250
Soggy Pasture	0	15	0	0	0	57	162	234
Total	53	188	57	36	32	207	201	70.41
								2

63 64

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	43	0	0	0	1	36	0	80
Wheat	0	130	4	0	0	0	20	154
Manmade Structures	0	14	44	0	0	13	4	75
Dirt Road	0	5	0	20	4	20	29	78
Pond	0	1	0	3	27	1	34	66
Healthy Pasture	10	8	1	11	0	115	0	145
Soggy Pasture	0	30	8	2	0	22	114	176
Total	53	188	57	36	32	207	201	63.70
								1

7 42

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	80	0	0	0	27	1	108
Manmade Structures	0	0	48	0	6	0	0	54
Dirt Road	0	0	0	33	0	0	0	33
Pond	0	2	9	3	26	0	1	41
Healthy Pasture	0	96	0	0	0	141	52	289
Soggy Pasture	0	10	0	0	0	39	147	196
Total	53	188	57	36	32	207	201	68.22
								1

54 63

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	50	0	0	0	0	0	0	50
Wheat	0	134	0	0	0	0	24	158
Manmade Structures	2	0	57	0	0	0	0	59
Dirt Road	0	0	0	30	1	0	1	32
Pond	1	0	0	5	31	0	0	37
Healthy Pasture	0	2	0	0	0	154	60	216
Soggy Pasture	0	52	0	1	0	53	116	222
Total	53	188	57	36	32	207	201	73.90
								2

42 54

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	131	0	0	0	0	22	153
Manmade Structures	0	0	55	1	2	0	1	59
Dirt Road	0	0	0	34	0	0	0	34
Pond	0	0	2	1	30	0	0	33
Healthy Pasture	0	0	0	0	0	149	49	198
Soggy Pasture	0	57	0	0	0	58	129	244
Total	53	188	57	36	32	207	201	75.06
								3

54 60

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	133	0	0	0	0	22	155
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	0	0	0	34	0	0	0	34
Pond	0	0	0	2	32	0	2	36
Healthy Pasture	0	1	0	0	0	156	63	220
Soggy Pasture	0	54	0	0	0	51	114	219
Total	53	188	57	36	32	207	201	74.81
								3

	42	64						
	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	52	0	0	0	5	0	0	57
Wheat	0	137	0	0	0	0	22	159
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	1	0	0	34	0	0	0	35
Pond	0	0	0	1	27	0	0	28
Healthy Pasture	0	3	0	0	0	171	58	232
Soggy Pasture	0	48	0	1	0	36	121	206
Total	53	188	57	36	32	207	201	77.39
								3

	60	64						
	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	143	0	0	0	4	24	171
Manmade Structures	0	0	44	3	0	0	4	51
Dirt Road	0	0	4	30	0	0	0	34
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	3	0	3	0	185	24	215
Soggy Pasture	0	42	9	0	0	18	149	218
Total	53	188	57	36	32	207	201	82.17
								3

	54	60						
	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	133	0	0	0	0	22	155
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	0	0	0	34	0	0	0	34
Pond	0	0	0	2	32	0	2	36
Healthy Pasture	0	1	0	0	0	156	63	220
Soggy Pasture	0	54	0	0	0	51	114	219
Total	53	188	57	36	32	207	201	74.81
								3

	4	42						
	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	84	0	0	0	51	7	142
Manmade Structures	0	0	54	0	9	0	0	63
Dirt Road	0	0	0	30	0	0	0	30
Pond	0	0	3	6	23	0	1	33
Healthy Pasture	0	99	0	0	0	132	65	296
Soggy Pasture	0	5	0	0	0	24	128	157
Total	53	188	57	36	32	207	201	65.12
								1

62 64

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	40	0	0	2	0	52	0	94
Wheat	0	130	0	0	0	0	15	145
Manmade Structures	0	8	57	0	0	41	0	106
Dirt Road	0	4	0	16	3	15	12	50
Pond	0	11	0	13	16	23	28	91
Healthy Pasture	13	0	0	4	9	68	0	94
Soggy Pasture	0	35	0	1	4	8	146	194
Total	53	188	57	36	32	207	201	61.11 1

54 64

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	52	0	0	0	0	0	0	52
Wheat	0	133	0	0	0	5	25	163
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	0	0	0	34	0	0	1	35
Pond	1	0	0	1	32	0	0	34
Healthy Pasture	0	0	0	0	0	161	55	216
Soggy Pasture	0	55	0	1	0	41	120	217
Total	53	188	57	36	32	207	201	76.10 3

Mean:	71.66
Std:	5.81
Mean + ½ std:	74.55
Mean - ½ std:	68.77

Table A-21: Panel Scene 2-Band SCR/LOG Stimuli/Response Matrices

64	**119**	**1**	**119**	**42**	**119**	**63**	**64**	**7**	**42**	**64**	**63**	**42**	**64**
0.25		0.25		0.25		0.25		0.25		0.25		0.25	
0	26	0	26	0	26	0	26	0	26	0	26	0	26
0	732	0	732	0	732	0	732	0	732	0	732	0	732
0.08		0.08		0.08		0.08		0.08		0.08		0.08	
0	26	0	26	26	0	0	26	0	26	0	26	0	26
3	729	47	685	732	0	0	732	0	732	2	730	0	732
0.05		0.05		0.05		0.05		0.05		0.05		0.05	
26	0	26	0	26	0	0	26	67	665	26	0	0	26
730	2	732	0	656	76	0	732	3.43	0	730	2	67	665
0.05		0.05		0.05		0.05		0.05		0.05		0.05	
26	0	26	0	26	0	26	0	26	0	26	0	26	0
0	732	1	731	0	732	7	725	1	731	0	732	0	732
0.1		0.1		0.1		0.1		0.1		0.1		0.1	
26	0	26	0	26	0	26	0	26	0	26	0	26	0
0	732	1	731	0	732	7	725	1	731	0	732	0	732
0.25		0.25		0.25		0.25		0.25		0.25		0.25	
26	0	26	0	26	0	26	0	26	0	26	0	26	0
0	732	1	731	0	732	5	727	1	731	0	732	0	732
42	**64**	**60**	**64**	**54**	**60**	**4**	**42**	**62**	**64**	**54**	**64**	**54**	**60**
0.25		0.25		0.25		0.25		0.25		0.25		0.25	
0	26	0	26	0	26	0	26	0	26	0	26	0	26
0	732	0	732	0	732	0	732	0	732	0	732	0	732
0.08		0.08		0.08		0.08		0.08		0.08		0.08	
0	26	0	26	0	26	0	26	0	26	0	26	26	0
3	729	208	524	0	732	0	732	0	732	0	732	732	0
0.05		0.05		0.05		0.05		0.05		0.05		0.05	
0	26	0	26	0	26	0	26	0	26	0	26	26	0
66	666	508	228	1	731	0	732	1	731	96	636	728	4
0.05		0.05		0.05		0.05		0.05		0.05		0.05	
26	0	26	0	26	0	26	0	26	0	26	0	26	0
0	732	0	732	0	732	0.	732	0	732	0	732	0	732
0.1		0.1		0.1		0.1		0.1		0.1		0.1	
26	0	26	0	26	0	26	0	26	0	26	0	26	0
0	732	0	732	0	732	0	732	0	732	0	732	0	732
0.25		0.25		0.25		0.25		0.25		0.25		0.25	
26	0	26	0	26	0	26	0	26	0	26	0	26	0
0	732	0	732	0	732	0	732	0	732	0	732	0	732

Table A-22: Panel Scene 2-Band SCR Analysis

64.00	119.00		1.00	119.00		42.00	119.00		63.00	64.00		7.00	42.00		54.00	63.00		42.00	54.00	
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	-0.00	0.00	0.06	-0.06	1.00	0.90	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	0.00	0.00	0.00
1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.09	0.91	1.00	1.00	0.00	0.00	0.09	-0.09
1.00	1.00	0.00			0.00			0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
		-0.00			-0.06			0.10			0.00			0.91			0.00			-0.09
		2.00			2.00			2.00			2.00			3.00			0.00			2.00

54.00	60.00		42.00	64.00		60.00	64.00		54.00	60.00		4.00	42.00		62.00	64.00		54.00	64.00	
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.00	0.99	0.01	0.00	0.00	-0.00	0.00	0.28	-0.28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	-0.01
1.00	1.00	0.00	0.00	0.09	-0.09	0.00	0.69	-0.69	0.00	0.00	-0.00	0.00	0.00	0.00	0.00	0.00	-0.00	0.00	0.13	-0.13
		0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
		0.01			-0.09			-0.98			-0.00			0.00			-0.00			-0.14
		2.00			2.00			1.00			2.00			2.00			2.00			2.00

Mean:	0.02
Std:	0.37
Mean + ½ std:	0.16
Mean - ½ std:	-0.21

Table A-23: Panel Scene 2-Band LOG Analysis

64.00	119.00		1.00	119.00		42.00	119.00		63.00	64.00		7.00	42.00		54.00	63.00		42.00	54.00	
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.01	0.99	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00
1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.01	0.99	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00
1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.01	0.99	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00
1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
		3.00			3.00			3.00			2.97			3.00			3.00			3.00
		3.00			2.00			3.00			1.00			2.00			3.00			3.00

54.00	60.00		42.00	64.00		60.00	64.00		54.00	60.00		4.00	42.00		62.00	64.00		54.00	64.00	
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00
1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00
1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00
1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
		3.00			3.00			3.00			3.00			3.00			3.00			3.00
		3.00			3.00			3.00			3.00			3.00			3.00			3.00

Mean:	2.99
Std:	0.007
Mean + ½ std:	3.00
Mean - ½ std:	2.99

Table A-24: Panel Scene 4-Band Results

Band Set		1	2	3
p1/clas1		tdiv orig/p1/clas 1	fsbs/p1/clas 1	tdiv mod/p1/clas 1
1	46	3	42	1
3	54	54	54	7
7	63	63	64	64
42	64	119	119	119
45	119			
		tdiv orig/p1/clas 2	fsbs/p1/clas 2	tdiv mod/p1/clas 2
		3	42	1
		54	54	7
		63	64	64
		119	119	119
		4	5	6
p2/clas2		tdiv orig/p2/clas 2	fsbs/p2/clas 2	tdiv mod/p2/clas 2
1	46	2	42	54
2	54	54	46	60
3	60	60	54	62
4	62	64	62	64
42	64			
7	8	9	10	11
sbf/p1	sbf/p2	tdiv orig/p1/tg	fsbs/p1/tg	tdiv mod/p1/tg
42	46	7	1	45
46	60	42	7	46
63	62	46	42	54
64	64	63	119	64
		12	13	14
		tdiv orig/p2/tg	fsbs/p2/tg	tdiv mod/p2/tg
		4	1	42
		42	4	46
		54	42	60
		62	64	64

Table A-25: Panel Scene 4-Band Gaussian Maximum Likelihood Confusion Matrices

1	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	1	4	0	0	0	0	58
Wheat	0	173	0	0	0	0	0	173
Manmade Structures	0	0	53	0	0	0	0	53
Dirt Road	0	0	0	36	0	0	0	36
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	0	0	0	0	158	61	219
Soggy Pasture	0	14	0	0	0	49	140	203
Total	53	188	57	36	32	207	201	83.33 3

2	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	5	0	0	0	0	58
Wheat	0	169	0	0	0	0	0	169
Manmade Structures	0	0	52	0	0	0	0	52
Dirt Road	0	0	0	36	0	0	0	36
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	0	0	0	0	157	54	211
Soggy Pasture	0	19	0	0	0	50	147	216
Total	53	188	57	36	32	207	201	83.46 3

3	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	4	0	0	0	0	57
Wheat	0	150	0	0	0	2	11	163
Manmade Structures	0	0	53	0	0	0	0	53
Dirt Road	0	0	0	36	0	1	1	38
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	14	0	0	0	167	42	223
Soggy Pasture	0	24	0	0	0	37	147	208
Total	53	188	57	36	32	207	201	82.43 3

4	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	2	1	0	0	0	56
Wheat	0	153	0	0	0	12	7	172
Manmade Structures	0	0	55	0	0	0	0	55
Dirt Road	0	0	0	34	0	0	1	35
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	0	0	0	0	163	61	224
Soggy Pasture	0	35	0	0	0	32	132	199
Total	53	188	57	35	32	207	201	80.36 2

5

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	5	0	0	0	0	58
Wheat	0	152	0	0	0	25	7	184
Manmade Structures	0	0	52	0	0	0	0	52
Dirt Road	0	0	0	35	0	0	1	36
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	0	0	0	0	162	50	212
Soggy Pasture	0	36	0	1	0	20	143	200
Total	53	188	57	36	32	207	201	81.27
								2

6

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	5	0	1	0	41	0	100
Wheat	0	128	0	0	0	8	16	152
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	0	0	0	34	0	0	1	35
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	3	0	0	0	141	57	201
Soggy Pasture	0	52	0	1	0	17	127	197
Total	53	188	57	36	32	207	201	73.90
								1

7

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	2	1	0	1	21	0	78
Wheat	0	134	0	0	0	9	20	163
Manmade Structures	0	0	56	1	0	0	0	57
Dirt Road	0	0	0	34	0	0	1	35
Pond	0	0	0	0	31	0	0	31
Healthy Pasture	0	5	0	0	0	153	29	187
Soggy Pasture	0	47	0	1	0	24	151	223
Total	53	188	57	36	32	207	201	79.07
								2

8

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	5	0	1	0	40	0	99
Wheat	0	139	0	0	0	7	18	164
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	0	0	0	34	0	0	0	34
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	4	0	0	0	146	60	210
Soggy Pasture	0	40	0	1	0	14	123	178
Total	53	188	57	36	32	207	201	75.45
								1

9

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	1	0	1	0	0	55
Wheat	0	162	0	0	0	2	4	168
Manmade Structures	0	0	56	1	0	0	0	57
Dirt Road	0	0	0	34	0	0	0	34
Pond	0	0	0	0	31	0	0	31
Healthy Pasture	0	4	0	0	0	157	48	209
Soggy Pasture	0	22	0	1	0	48	149	220
Total	53	188	57	36	32	207	201	82.95 3

10

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	4	0	0	0	0	57
Wheat	0	72	0	0	0	21	1	94
Manmade Structures	0	0	53	0	0	0	0	53
Dirt Road	0	0	0	36	0	0	0	36
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	100	0	0	0	127	42	269
Soggy Pasture	0	16	0	0	0	59	158	233
Total	53	188	57	36	32	207	201	68.60 1

11

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	154	0	0	0	16	26	196
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	0	0	0	35	0	0	1	36
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	1	0	0	0	159	54	214
Soggy Pasture	0	33	0	1	0	32	120	186
Total	53	188	57	36	32	207	201	78.81 2

12

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	0	0	0	53
Wheat	0	169	0	0	0	10	5	184
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	0	0	0	35	0	0	1	36
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	0	0	0	0	166	45	211
Soggy Pasture	0	19	0	1	0	31	150	201
Total	53	188	57	36	32	207	201	85.53 3

13

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	1	5	0	0	11	0	70
Wheat	0	162	0	0	0	10	2	174
Manmade Structures	0	0	52	0	0	0	0	52
Dirt Road	0	0	0	36	0	0	0	36
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	7	0	0	0	177	54	238
Soggy Pasture	0	18	0	0	0	9	145	172
Total	53	188	57	36	32	207	201	84.88
								3

14

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	53	0	0	0	1	0	0	54
Wheat	0	137	0	0	0	17	16	170
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	0	0	0	35	0	0	1	36
Pond	0	0	0	0	31	0	0	31
Healthy Pasture	0	1	0	0	0	163	55	219
Soggy Pasture	0	50	0	1	0	27	129	207
Total	53	188	57	36	32	207	201	78.17
								2

15

	Paved Road	Wheat	Manmade Structures	Dirt Road	Pond	Healthy Pasture	Soggy Pasture	Total
Paved Road	52	0	0	0	0	0	0	52
Wheat	0	135	0	0	0	4	25	164
Manmade Structures	0	0	57	0	0	0	0	57
Dirt Road	1	0	0	35	0	0	1	37
Pond	0	0	0	0	32	0	0	32
Healthy Pasture	0	2	0	0	0	175	47	224
Soggy Pasture	0	51	0	1	0	28	128	208
Total	53	188	57	36	32	207	201	79.33
								2

Mean:	79.87
Std:	4.70
Mean + ½ std:	82.22
Mean - ½ std:	77.52

Table A-26: Panel Scene 4-Band SCR/LOG Stimuli/Response Matrices

	1		2		3		4		5		6		7	
SCR														
0.25														
	0	26	0	26	0	26	0	26	0	26	0	26	0	26
	0	732	0	732	0	732	0	732	0	732	0	732	0	732
0.005														
	26	0	0	26	0	26	25	1	0	26	0	26	0	26
	505	227	2	730	2	730	338	394	0	732	280	452	0	732
0.001														
	26	0	26	0	26	0	26	0	0	26	26	0	0	26
	730	2	730	2	77	655	732	0	16	716	729	3	32	700
LOG														
0.05														
	26	0	26	0	26	0	26	0	26	0	26	0	26	0
	0	732	0	732	0	732	0	732	0	732	0	732	0	732

8		9		10		11		12		13		14	
0	26	0	26	0	26	0	26	0	26	0	26	0	26
0	732	0	732	0	732	0	732	0	732	0	732	0	732
0	26	26	0	0	26	0	26	0	26	26	0	0	26
144	588	732	0	3	729	0	732	0	732	93	639	0	732
26	0	0	26	26	0	0	26	0	26	26	0	0	26
729	3	54	678	64	668	0	732	102	630	715	17	106	626
26	0	26	0	26	0	26	0	26	0	26	0	26	0
0	732	0	732	0	732	0	732	0	732	0	732	0	732

Table A-27: Panel Scene 4-Band SCR Analysis

1.00			2.00			3.00			4.00			5.00			6.00			7.00		
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.00	0.69	0.31	0.00	0.00	-0.00	0.00	0.00	-0.00	0.96	0.46	0.50	0.00	0.00	0.00	0.00	0.38	-0.38	0.00	0.00	0.00
1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.11	0.89	1.00	1.00	0.00	0.00	0.02	-0.02	1.00	1.00	0.00	0.00	0.04	-0.04
1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00			0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
		0.31			0.00			0.89			0.50			-0.02			-0.38			-0.04
		2.00			2.00			3.00			3.00			2.00			1.00			2.00

8.00			9.00			10.00			11.00			12.00			13.00			14.00		
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.20	-0.20	0.00	0.07	-0.07	0.00	0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.13	0.87	0.00	0.00	0.00
1.00	1.00	0.00	1.00	1.00	0.00	1.00	0.09	0.91	0.00	0.00	0.00	0.00	0.14	-0.14	1.00	0.98	0.02	0.00	0.14	-0.14
1.00	1.00	0.00			0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
		-0.19			-0.07			0.91			0.00			-0.14			0.90			-0.14
		3.00			1.00			3.00			2.00			1.00			3.00			1.00

Mean:	0.16
Std:	0.43
Mean + ½ std:	0.38
Mean - ½ std:	-0.05

Table A-28: Pasture Scene 4-Band Results

p1/clas 1		tdiv orig/p1/clas 1	tdiv mod/p1/clas 1	fsbs/p1/clas 1
1	57	71	71	55
2	61	84	84	84
3	62			
4	63			
5	64			
8	65	tdiv orig/p1/clas 2	tdiv mod/p1/clas 2	fsbs/p1/clas 2
37	66			
53	70	57	57	55
54	71	61	61	84
55	84			

p2/clas 2		tdiv orig/p2/clas 2	tdiv mod/p2/clas 2	fsbs/p2/clas 2
1	57	57	57	61
3	61	61	61	83
53	62			
54	63			
55	83	tdiv orig/p2/tg	tdiv mod/p2/tg	fsbs/p2/tg
p1a/clas1		63	63	62
		83	83	83
54				
55				
61				
62				
71		tdiv orig/p1/tg	tdiv/p1/tg	fsbs/p1/tg
		66	66	62
		70	70	84

sbf_int/p1	sbf_int/p1a	sbf_int/p2
53	61	53
54	71	54

presc/clas1	presc/tg	presc/clas2
54	54	54
71	64	83

tdiv orig/p1a/clas1	fsbs/p1a/clas1	tdiv mod/p1a/clas1

Table A-29: Pasture Scene 2-Band Gaussian Likelihood Confusion Matrices

71 84

	pasture	water	unknown	wheat1	wheat2	total
pasture	233	0	0	9	9	251
water	0	60	0	0	0	60
unknown	1	0	98	0	0	99
wheat1	1	0	0	233	12	246
wheat2	0	0	0	45	85	130
total	235	60	98	287	106	90.20
						2

55 84

	pasture	water	unknown	wheat1	wheat2	total
pasture	232	0	0	9	0	241
water	0	59	0	0	0	59
unknown	2	0	98	0	0	100
wheat1	1	0	0	276	0	277
wheat2	0	1	0	2	106	109
total	235	60	98	287	106	98.09
						3

62 84

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	0	0	7	10	252
water	0	60	0	0	0	60
unknown	0	0	98	0	0	98
wheat1	0	0	0	202	8	210
wheat2	0	0	0	78	88	166
total	235	60	98	287	106	86.90
						2

66 70

	pasture	water	unknown	wheat1	wheat2	total
pasture	207	0	0	14	3	224
water	0	60	0	0	0	60
unknown	27	0	98	0	0	125
wheat1	0	0	0	215	51	266
wheat2	0	0	0	58	52	110
total	234	60	98	287	106	80.41
						1

57 61

	pasture	water	unknown	wheat1	wheat2	total
pasture	227	0	2	10	0	239
water	0	55	0	0	10	65
unknown	0	0	93	0	0	93
wheat1	0	1	3	277	8	289
wheat2	8	4	0	0	96	108
total	235	60	98	287	114	95.17
						3

61 83

	pasture	water	unknown	wheat1	wheat2	total
pasture	234	0	0	10	12	256
water	0	60	0	0	0	60
unknown	0	0	98	0	0	98
wheat1	1	0	0	194	11	206
wheat2	0	0	0	83	83	166
total	235	60	98	287	106	85.11
						1

63 83

	pasture	water	unknown	wheat1	wheat2	total
pasture	233	0	0	8	11	252
water	0	60	0	0	0	60
unknown	0	0	98	0	0	98
wheat1	2	0	0	197	6	205
wheat2	0	0	0	82	89	171
total	235	60	98	287	106	86.13
						1

62 83

	pasture	water	unknown	wheat1	wheat2	total
pasture	233	0	0	7	8	248
water	0	60	0	0	0	60
unknown	0	0	98	0	0	98
wheat1	2	0	0	226	30	258
wheat2	0	0	0	54	68	122
total	235	60	98	287	106	87.15
						2

Mean:	89.76
Std:	6.51
Mean + ½ std:	93.02
Mean - ½ std:	86.51

		54	71				
	pasture	water	unknown	wheat1	wheat2	total	
pasture	230	0	2	7	0	239	
water	0	56	0	0	0	56	
unknown	0	0	94	0	0	94	
wheat1	5	0	2	280	0	287	
wheat2	0	4	0	0	106	110	
total	235	60	98	287	106	97.46	
						3	

		54	83			
	pasture	water	unknown	wheat1	wheat2	total
pasture	232	0	1	8	0	241
water	0	59	0	0	0	59
unknown	1	0	97	0	0	98
wheat1	2	0	0	277	0	279
wheat2	0	1	0	2	106	109
total	235	60	98	287	106	98.09
						3

		61	71			
	pasture	water	unknown	wheat1	wheat2	total
pasture	232	0	0	6	11	249
water	0	60	0	0	0	60
unknown	3	0	98	0	0	101
wheat1	0	0	0	244	19	263
wheat2	0	0	0	37	76	113
total	235	60	98	287	106	90.33
						2

		63	54			
	pasture	water	unknown	wheat1	wheat2	total
pasture	186	0	0	47	0	233
water	3	52	8	1	19	83
unknown	0	3	90	0	0	93
wheat1	43	5	0	205	4	257
wheat2	3	0	0	34	83	120
total	235	60	98	287	106	78.37
						1

		54	64			
	pasture	water	unknown	wheat1	wheat2	total
pasture	225	0	2	9	0	236
water	0	53	0	0	20	73
unknown	0	0	93	0	0	93
wheat1	10	3	3	278	0	294
wheat2	0	4	0	0	86	90
total	235	60	98	287	106	93.51
						3

Table A-30: Pasture Scene 2-Band SCR/LOG Stimuli/Response Matrices

57	61	61	83	63	83	62	83	54	71	54	83	61	71	53	54	54	64	71	84	55	84	66	70	62	84
0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25			
																								0.25	
58	20	58	20	58	20	58	20	3	75	0	78	0	78	0	78	58	20	60	18	0	78	0	78		
100	170	111	159	186	84	195	75	153	117	184	86	0	270	0	270	109	161	191	79	184	86	0	270	58	20
																								190	80
0.5		0.5		0.5		0.5		0.5		0.5		0.5		0.5		0.5		0.5		0.5		0.5		0.5	
0	78	0	78	0	78	0	78	0	78	0	78	0	78	0	78	0	78	0	78	0	78	0	78	0	78
29	241	0	270	28	242	33	237	26	244	40	230	0	270	0	270	25	245	41	229	39	231	0	270	29	241
0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1	
78	0	69	9	75	3	65	13	78	0	67	11	58	20	0	78	78	0	78	0	71	7	0	78	64	14
270	0	270	0	270	0	270	0	270	0	270	0	9	261	0	270	270	0	270	0	270	0	10	260	270	0
0.05		0.05		0.05		0.05		0.05		0.05		0.05		0.05		0.05		0.05		0.05		0.05		0.05	
78	0	78	0	78	0	78	0	74	4	72	6	76	2	78	0	78	0	78	0	78	0	78	0	78	0
71	199	39	231	45	225	37	233	27	388	5	410	0	415	96	174	69	201	42	228	47	223	35	235	38	232
0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1		0.1	
78	0	78	0	78	0	78	0	73	5	72	6	76	2	76	2	78	0	78	0	78	0	78	0	78	0
66	204	23	247	36	234	20	250	26	389	4	411	0	415	68	204	66	204	53	217	36	234	23	247	19	251
0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25		0.25	
76	0	0	78	78	0	78	0	72	6	71	7	75	3	76	2	78	0	78	0	78	0	78	0	78	0
51	219	270	0	8	262	1	269	22	393	1	414	0	415	47	223	54	216	6	264	29	241	2	268	0	270

Table A-31: Pasture Scene 2-Band SCR Analysis

57.00	61.00		61.00	83.00		63.00	83.00		62.00	83.00		54.00	71.00		54.00	83.00		61.00	71.00	
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.74	0.37	0.37	0.74	0.41	0.33	0.74	0.69	0.05	0.74	0.72	0.02	0.04	0.57	-0.53	0.00	0.68	-0.68	0.00	0.00	0.00
0.00	0.11	-0.11	0.00	0.00	0.00	0.00	0.10	-0.10	0.00	0.12	-0.12	0.00	0.10	-0.10	0.00	0.15	-0.15	0.00	0.00	0.00
1.00	1.00	0.00	0.88	1.00	-0.12	0.96	1.00	-0.04	0.83	1.00	-0.17	1.00	1.00	0.00	0.86	1.00	-0.14	0.74	0.03	0.71
		0.27			0.22			-0.09			-0.27			-0.62			-0.97			0.71
		3.00			3.00			2.00			2.00			1.00			1.00			3.00

53.00	54.00		54.00	64.00		71.00	84.00		55.00	84.00		66.00	70.00		62.00	84.00	
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.74	0.40	0.34	0.77	0.71	0.06	0.00	0.68	-0.68	0.00	0.00	0.00	0.74	0.70	0.04
0.00	0.00	0.00	0.00	0.09	-0.09	0.00	0.15	-0.15	0.00	0.14	-0.14	0.00	0.00	0.00	0.00	0.11	-0.11
0.00	0.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	0.91	1.00	-0.09	0.00	0.04	-0.04	0.82	1.00	-0.18
		0.00			0.25			-0.09			-0.92			-0.04			-0.25
		2.00			3.00			2.00			1.00			2.00			2.00

Mean:	-0.14
Std:	0.48
Mean + ½ std:	0.10
Mean - ½ std:	-0.38

Table A-32: Pasture Scene 2-Band LOG Analysis

57.00	61.00		61.00	83.00		63.00	83.00		62.00	83.00		54.00	71.00		54.00	83.00		61.00	71.00	
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
1.00	0.26	0.74	1.00	0.14	0.88	1.00	0.17	0.83	1.00	0.14	0.86	0.95	0.10	0.85	0.92	0.02	0.90	0.97	0.00	0.97
1.00	0.24	0.76	1.00	0.09	0.91	1.00	0.13	0.87	1.00	0.07	0.93	0.94	0.10	0.84	0.92	0.01	0.91	0.97	0.00	0.97
1.00	0.19	0.81	0.00	1.00	-1.00	1.00	0.03	0.97	1.00	0.00	1.00	0.92	0.08	0.84	0.91	0.00	0.91	0.96	0.00	0.96
		2.30			0.77			2.67			2.79			2.53			2.72			2.91
		2.00			1.00			2.00			3.00			2.00			3.00			3.00
53.00	54.00		54.00	64.00		71.00	84.00		55.00	84.00		66.00	70.00		62.00	84.00				
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm				
1.00	0.36	0.64	1.00	0.26	0.74	1.00	0.54	0.46	1.00	0.17	0.83	1.00	0.13	0.87	1.00	0.14	0.86			
0.97	0.24	0.73	1.00	0.24	0.76	1.00	0.68	0.32	1.00	0.13	0.87	1.00	0.09	0.91	1.00	0.07	0.93			
0.97	0.17	0.80	1.00	0.20	0.80	1.00	0.02	0.98	1.00	0.11	0.89	1.00	0.01	0.99	1.00	0.00	1.00			
		2.17			2.30			1.76			2.59			2.78			2.79			
		2.00			2.00			1.00			2.00			3.00			3.00			

Mean:	2.39
Std:	0.58
Mean + ½ std:	2.68
Mean - ½ std:	2.10

Table A-33: Pasture Scene 4-Band Results

p1/clas1		1	2	3
		tdiv orig/p1/clas1	fsbs/p1/clas1	tdiv mod/p1/clas1
1	55			
3	61	3	54	55
4	62	53	55	61
53	63	63	61	62
54	71	71	71	71

p2/clas2		4		
		tdiv orig/p1/clas2	fsbs/p1/clas2	tdiv mod/p1/clas2
1	57			
3	61	1	54	55
53	62	3	55	61
54	63	53	61	62
55	83	71	71	71

8	9	5	6	7
sbf/p2	sbf/p1	tdiv orig/p2/clas2	fsbs/p2/clas2	tdiv mod/p2/clas2
61	61	1	54	57
62	62	3	57	61
63	63	54	61	62
83	71	83	83	83

	15		10	11
pres/clas1	pres/clas2	tdiv orig/p1/tg	fsbs/p1/tg	tdiv mod/p1/tg
54	54	3	54	3
55	55	53	55	62
61	61	63	62	63
71	83	71	71	71

12	13	14
tdiv orig/p2/tg	fsbs/p2/tg	tdiv mod/p2/tg
3	57	3
54	62	62
63	63	63
83	83	83

Table A-34: Pasture Scene 4-Band Gaussian Maximum Likelihood Confusion Matrices

1

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	0	6	18	0	259
water	0	60	0	0	0	60
unknown	0	0	92	0	0	92
wheat1	0	0	0	269	0	269
wheat2	0	0	0	45	106	151
total	235	60	98	332	106	96.95
						3

2

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	0	6	9	2	252
water	0	60	0	0	0	60
unknown	0	0	92	0	0	92
wheat1	0	0	0	278	3	281
wheat2	0	0	0	45	101	146
total	235	60	98	332	106	97.46
						3

3

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	0	6	9	3	253
water	0	60	0	0	0	60
unknown	0	0	92	0	0	92
wheat1	0	0	0	278	2	280
wheat2	0	0	0	0	101	101
total	235	60	98	287	106	97.46
						3

4

	pasture	water	unknown	wheat1	wheat2	total
pasture	229	0	5	15	2	251
water	0	59	0	0	0	59
unknown	0	0	93	0	0	93
wheat1	6	1	0	272	5	284
wheat2	0	0	0	45	99	144
total	235	60	98	332	106	95.67
						2

5

	pasture	water	unknown	wheat1	wheat2	total
pasture	233	0	2	15	2	252
water	0	59	0	0	0	59
unknown	1	0	96	0	0	97
wheat1	1	1	0	271	7	280
wheat2	0	0	0	1	97	98
total	235	60	98	287	106	96.18
						2

6

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	3	6	12	3	259
water	0	57	0	0	0	57
unknown	0	0	92	0	0	92
wheat1	0	0	0	275	0	275
wheat2	0	0	0	0	103	103
total	235	60	98	287	106	96.95
						3

7

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	0	6	11	3	255
water	0	60	0	0	0	60
unknown	0	0	92	0	0	92
wheat1	0	0	0	276	1	277
wheat2	0	0	0	0	102	102
total	235	60	98	287	106	97.33
						3

8

	pasture	water	unknown	wheat1	wheat2	total
pasture	233	0	2	9	14	258
water	0	60	0	0	0	60
unknown	0	0	96	0	0	96
wheat1	2	0	0	243	20	265
wheat2	0	0	0	35	72	107
total	235	60	98	287	106	89.57
						1

9

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	0	3	9	11	258
water	0	60	0	0	0	60
unknown	0	0	95	0	0	95
wheat1	0	0	0	263	20	283
wheat2	0	0	0	15	75	90
total	235	60	98	287	106	92.62
						1

10

	pasture	water	unknown	wheat1	wheat2	total
pasture	230	3	6	7	1	247
water	0	57	0	0	0	57
unknown	0	0	92	0	0	92
wheat1	5	0	0	280	2	287
wheat2	0	0	0	0	103	103
total	235	60	98	287	106	96.95
						3

11

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	0	0	9	9	253
water	0	60	0	0	0	60
unknown	0	0	98	0	0	98
wheat1	0	0	0	267	15	282
wheat2	0	0	0	11	82	93
total	235	60	98	287	106	94.40
						2

12

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	3	6	17	1	262
water	0	57	0	0	0	57
unknown	0	0	92	0	0	92
wheat1	0	0	0	270	1	271
wheat2	0	0	0	45	104	149
total	235	60	98	332	106	96.44
						2

13

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	2	6	10	3	256
water	0	58	0	0	0	58
unknown	0	0	92	0	0	92
wheat1	0	0	0	277	1	278
wheat2	0	0	0	45	102	147
total	235	60	98	332	106	97.20
						3

14

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	0	0	9	10	254
water	0	60	0	0	0	60
unknown	0	0	98	0	0	98
wheat1	0	0	0	255	13	268
wheat2	0	0	0	23	83	106
total	235	60	98	287	106	93.00
						1

15

	pasture	water	unknown	wheat1	wheat2	total
pasture	235	0	3	7	0	245
water	0	50	0	0	0	50
unknown	0	0	95	0	0	95
wheat1	0	0	0	232	2	234
wheat2	0	10	0	48	104	162
total	235	60	98	287	106	91.09
						1

Mean:	95.58
Std:	2.36
Mean + ½ std:	96.76
Mean - ½ std:	94.40

Table A-35: Pasture Scene 4-Band SCR/LOG Stimuli/Response Matrices

	1		2		3		4		5		6		7		8	
SCR																
0.25																
	0	78	0	78	0	78	0	78	0	78	70	8	64	14	58	20
	0	270	0	270	0	270	0	270	19	251	45	225	27	243	2	268
0.05																
	73	5	2	76	60	18	62	16	73	5	78	0	78	0	78	0
	204	66	5	265	217	53	192	78	266	4	270	0	270	0	253	17
0.1																
	58	20	0	78	58	20	1	77	50	28	78	0	78	0	64	14
	58	212	0	270	37	233	51	219	116	154	263	7	226	44	122	148
LOG																
0.05																
	78	0	78	0	78	0	78	0	78	0	78	0	78	0	78	0
	31	239	0	270	2	268	30	240	23	247	11	259	19	251	23	247
0.005																
	78	0	78	0	78	0	78	0	78	0	78	0	78	0	78	0
	40	230	2	268	4	266	39	231	36	234	46	224	27	243	28	242
0.15																
	78	0	78	0	78	0	78	0	78	0	78	0	78	0	78	0
	270	0	0	270	0	270	13	257	0	268	0	270	0	270	0	270

	9		10		11		12		13		14		15	
	0	78	0	78	0	78	62	16	64	14	61	17	0	78
	0	270	0	270	0	270	24	246	26	244	2	268	0	270
	59	19	1	77	60	18	78	0	78	0	78	0	66	12
	227	43	5	265	197	73	270	0	270	0	266	4	5	265
	58	20	0	78	58	20	78	0	0	78	77	1	0	78
	54	216	0	270	25	245	190	80	0	270	195	75	0	270
	78	0	78	0	78	0	78	0	78	0	78	0	78	0
	23	247	1	269	15	255	31	239	14	256	22	248	265	5
	78	0	78	0	78	0	78	0	78	0	78	0	78	0
	27	243	1	269	27	243	41	229	21	249	28	242	41	229
	78	0	78	0	78	0	78	0	78	0	78	0	78	0
	13	257	0	270	0	270	0	270	0	270	0	270	0	270

Table A-36: Pasture Scene 4-Band SCR Analysis

1.00			2.00			3.00			4.00			5.00			6.00			7.00			8.00		
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm.		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	-0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.74	0.01	0.74
0.94	0.76	0.18	0.00	0.00	0.00	0.74	0.14	0.61	0.01	0.19	-0.18	0.64	0.43	0.21	0.90	0.17	0.73	0.82	0.10	0.72	0.82	0.45	0.37
0.74	0.21	0.53	0.03	0.02	0.01	0.77	0.80	-0.03	0.79	0.71	0.08	0.94	0.99	-0.05	1.00	0.97	0.03	1.00	0.84	0.16	1.00	0.94	0.06
1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
		0.71			0.01			0.57			-0.09			0.09			0.76			0.88		2.40	
		2.00			1.00			2.00			1.00			1.00			2.00			2.00			3.00

9.00			10.00			11.00			12.00			13.00			14.00			15.00		
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
																		0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.85	0.02	0.83
0.74	0.20	0.54	0.00	0.00	0.00	0.74	0.09	0.65	0.79	0.09	0.71	0.82	0.10	0.72	0.78	0.01	0.77	0.00	0.00	0.00
0.76	0.84	-0.08	0.01	0.02	-0.01	0.77	0.73	0.04	1.00	0.70	0.30	1.00	1.00	0.00	0.99	0.72	0.26			0.00
1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00			0.00	1.00	0.99	0.01			
		0.46			-0.01			0.69			1.00			0.72			1.05			0.83
		2.00			1.00			2.00			3.00			2.00			3.00			2.00

Mean:	0.67
Std:	0.61
Mean + ½ std:	0.98
Mean - ½ std:	0.37

Table A-37: Pasture Scene 4-Band LOG Analysis

1.00			2.00			3.00			4.00			5.00			6.00			7.00			8.00		
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.00	0.11	0.89	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.05	0.95	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00
1.00	0.15	0.85	1.00	0.00	1.00	1.00	0.01	0.99	1.00	0.11	0.89	1.00	0.09	0.91	1.00	0.04	0.96	1.00	0.07	0.93	1.00	0.09	0.91
1.00	1.00	0.00	1.00	0.01	0.99	1.00	0.01	0.99	1.00	0.14	0.86	1.00	0.13	0.87	1.00	0.17	0.83	1.00	0.10	0.90	1.00	0.10	0.90
		1.74			2.99			2.98			2.70			2.78			2.79			2.83			2.81
		1.00			3.00			3.00			2.00			2.00			2.00			2.00			2.00

9.00			10.00			11.00			12.00			13.00			14.00			15.00		
Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm		Hit	False Alarm	
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.02	0.98
1.00	0.05	0.95	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.15	0.85
1.00	0.09	0.91	1.00	0.00	1.00	1.00	0.06	0.94	1.00	0.11	0.89	1.00	0.05	0.95	1.00	0.08	0.92	1.00	0.00	1.00
1.00	0.10	0.90	1.00	0.00	1.00	1.00	0.10	0.90	1.00	0.15	0.85	1.00	0.08	0.92	1.00	0.10	0.90			0.00
		2.77			2.99			2.84			2.73			2.87			2.81			2.83
		2.00			3.00			2.00			2.00			2.00			2.00			2.00

Mean:	2.76
Std:	0.30
Mean + ½ std:	2.91
Mean - ½ std:	2.61

Appendix B

```
; IDL COVARIANCE FUNCTION - J. Laurenzano (1997)

; This function was designed specifically to
; develop a covariance matrix for an input class training sample
; (#pixels x #bands)

Function cl_cov,class1
On_error, 1
temp=size(class1)

if(temp(2) EQ 1) then begin
        temp2=moment(class1)
        return, temp2(1)
endif else return, correlate(transpose(class1),/covariance)

END

; IDL CLASS MEAN FUNCTION - J. Laurenzano (1997)

; This function is intended to determine the class
; mean vector for an input class training sample
; (#pixels x #bands). The output vector consists of the
; mean value for each band represented in the sample.

FUNCTION cl_mean, class1
;On_error,1
temp=size(class1)
;print, 'temp', temp
if (temp(0) eq 1) then number=1 $
  else number=temp(temp(0))

nx=n_elements(class1(*,0))
muoc=dblarr(number)

for i=0,number-1 do begin
        muoc(i)=total(class1(*,i))/nx
endfor

return, muoc
END
```

```
; ENVI/IDL THRESHOLDED DIVERGENCE BAND SELECTION - J. Laurenzano (1997)
; (based on Rosenblum, 1990)

; TDIV inputs class training samples, number of bands desired in the
; output spectral subset, and probability misclassification (generally
; assumed to be 1.0 e-15  (Rosenblum, 1997)) The band names of the
; optimal subset are output.  Original TD includes the statement (if(dr(0) GT 1) then dr=1).

;************************************************************************
pro quit_event, event

  widget_control, event.top, /destroy

end

pro tdiv_doit, fid=fid,pos=pos,dims=dims, out_name=out_name,$
  numbands=numbands, prob=prob, in_memory=in_memory, r_fid=r_fid

T=systime(1)

  print, pos


envi_file_query, fid, fname=fname, nb=nb, ns=ns,nl=nl, $
  bnames=bnames, xstart=xstart, ystart=ystart
  print, bnames
  temp=size(pos)
  nb=temp(1)


;Allocate memory array or open output file
get_lun, unit
if(in_memory) then mem_res=strarr(numbands) $
  else openw, unit, out_name
;stop
; Determine all possible spectral band subsets
temp_arr=intarr(nb, numbands)
temp_arr(*,0)=pos
for i=1,numbands-1 do temp_arr(*,i)=shift(temp_arr(*,i-1),-1)

subset=intarr(nb*(numbands-1), numbands)
combination=intarr(nb*(numbands-1),numbands)
count=0
while (count LT numbands-1) do begin
  subset(count*nb:count*nb+(nb-1), *)=temp_arr
  for j=0,count do $
```

```
  temp_arr(*,(numbands-1)-j)=shift(temp_arr(*,(numbands-1)-j),-1)
 count=count+1
endwhile

; Determine divergence value for each possible spectral subset

sub_size=size(subset)
th_div=dblarr(sub_size(1))
envi_report_setup, fname=fname, out_name=out_name, in_memory=0, $
 title='Thresholded Divergence Calculation', base=rbase, /interupt
envi_report_inc, rbase,sub_size(1)

for q=0,sub_size(1)-1 do begin
print, 'total iterations', sub_size(1)-1
envi_report_stat, rbase, q, sub_size(1), cancel=cancel
if(cancel) then begin
 !error=envi_cancel_val()
 goto, trouble
endif

;stop
newpos=intarr(numbands)
newpos=subset(q,*)
temp=newpos(sort(newpos))

; check for bad and repeat combinations
a_test=n_elements(uniq(newpos))

m=0
check=0
while (m LT nb*(numbands-1)) do begin
 now=combination(m,*)
 ;stop
 snow=where(now eq temp)
 if(n_elements(snow) eq n_elements(temp)) then begin
 m=nb*(numbands-1)
 check=1
 endif else m=m+1
endwhile

if(a_test eq numbands) AND (check EQ 0) then begin
print, 'q', q
print, 'newpos', newpos
;stop
```

```
; Acquire class sample information
roi_ids=envi_get_roi_ids(fid=fid)

numclass=n_elements(roi_ids)
div=dblarr(numclass,numclass)

for i=0, numclass-1 do begin
 for j=0, numclass-1 do begin
  ; Form class matrices
  roi_addr_1=envi_get_roi(roi_ids(i), roi_name=name, roi_color=color)
  roi_addr_2=envi_get_roi(roi_ids(j), roi_name=name, roi_color=color)
  class1=dblarr(n_elements(roi_addr_1),nb)
  class1=transpose(envi_get_roi_data(roi_ids(i), fid=fid, pos=newpos))
  class2=dblarr(n_elements(roi_addr_2),nb)
  class2=transpose(envi_get_roi_data(roi_ids(j), fid=fid, pos=newpos))

  ; Calculate class statistics
  amean=cl_mean(class1)
  bmean=cl_mean(class2)
  bcov=cl_cov(class2)

  ; Calculate threshold value
  dt=(-2.)*alog(prob/((2.*!pi)^(numbands/2.)))
  ; Calculate ratio value
  dr=((transpose(amean-bmean)#invert(bcov)#(amean-bmean)) + $
   alog(determ(bcov)))/dt


  ;
 ;if(dr(0) GT 1) then dr=1

  div(i,j)=dr

 endfor ; end of class loop (i)

endfor ;end of class loop(j)
; sum matrix elements and insert sum into th_div array

th_div(q)=total(div)
combination(q,*)=temp
endif else th_div(q)=0
print, 'th_div',th_div(q)
endfor ;end of subset loop (q)
!error=0
trouble: if(!error NE 0) then envi_io_error, $
 'Thresholded Divergence Processing', unit=unit
```

```
print, 'th_div',th_div
;stop
b=max(th_div)
temp=where(th_div eq b)
b_size=n_elements(temp)
if(b_size GT 1) then print,'Multiple subsets'

;print,'best',best
;print, subset(best,*)
print, bnames(subset(temp,*))
result=bnames(subset(temp,*))

Time_diff=systime(1)-T
Print, Time_diff, 'Seconds'

; Allocate Memory array or open output file
get_lun, unit
if(in_memory) then mem_res=strarr(b_size,numbands) $
  else openw, unit, out_name
if(in_memory) then mem_res=bnames(subset(temp, *)) $
  else printf, unit, bnames(subset(temp, *))
free_lun, unit

; Construct widget output
base=widget_base(title='Band Selection Output', /column, xsize=300, $
  xoff=200, yoff=200)
quit=widget_button(base, value='Done', event_pro='quit_event')
list=widget_table(base, value=result, uvalue='list', ysize=numbands,$
  xsize=b_size)
widget_control, base, /realize
xmanager, 'wlist', base

end

;************************************************************************
pro tdiv, ev

widget_control, ev.id, get_uvalue=uvalue
if (uvalue eq 'divergence') then begin

  ; Get input file
  envi_select, title='Thresholded Divergence Input File', fid=fid, $
    dims=dims, pos=pos, /mask, /roi

  if (fid eq -1) then return
```

```
if (fid eq -1) then return

; Widget for input parameters
envi_center, xoff, yoff
base=widget_auto_base( title='Thresholded Divergence Input Parameters')
sb=widget_base(base, /column, /frame)
sb1=widget_base(sb, /row)

wp=widget_param(sb1, prompt='Number of bands in spectral subset',$
  dt=2, xs=6, uvalue='numbands', ceil=n_elements(pos), $
  default=n_elements(pos)/2.0, /auto)
sb1=widget_base(sb, /row)
wp=widget_param(sb1, prompt='Probability of Misclassification', $
  dt=4, xs=20, uvalue='prob',field=6, /auto)
sb=widget_base(base, /column, /frame)
ofw=widget_outfm(sb, func='envi_out_check', uvalue='outf', /auto)
; Automanage the widget
result=auto_wid_mng(base)
if(result.accept eq 0) then return
numbands=result.numbands
print, numbands
prob=result.prob
print, prob

tdiv_doit, fid=fid, pos=pos, numbands=numbands, prob=prob, $
  out_name=result.outf.name, in_memory=result.outf.in_memory
endif
end
```

```
; ENVI/IDL FORWARD SEQUENTIAL BAND SELECTION - J. Laurenzano (1997)
; (adapted from Hardie, 1994)

; FSBS inputs class training samples and the number of bands
; (numbands) desired in the output spectral subset.  Optimal
; spectral bands are determined using an iterative process
; based on the Bhattacharyya Distance.
;*******************************************************************
pro quit_event, event
  widget_control, event.top, /destroy
end

pro fsbs_doit, fid=fid,pos=pos,dims=dims, out_name=out_name,$
  numbands=numbands, in_memory=in_memory, r_fid=r_fid
  print, 'pos',pos

envi_file_query, fid, fname=fname, nb=nb, ns=ns,nl=nl, $
  bnames=bnames, xstart=xstart, ystart=ystart
  print, bnames(pos)

;stop
temp=size(pos)
nb=temp(1)

;Allocate memory array or open output file
get_lun, unit
if(in_memory) then mem_res=strarr(numbands) $
  else openw, unit, out_name

; Define relevant variables
mband=fltarr(numbands)
maxb=dblarr(numbands)
; Acquire class sample information
roi_ids=envi_get_roi_ids(fid=fid)
numclass=n_elements(roi_ids)
B_matrix=dblarr(numclass,numclass)
; Establish Status Bar
envi_report_setup, fname=fname, out_name=out_name, $
  in_memory=0, title='Forward Sequential Band Selection', $
  base=rbase, /interupt
envi_report_inc, rbase, numbands

; Begin sequential band selection
for j=0,numbands-1 do begin
  envi_report_stat, rbase, j, numbands, $
     cancel=cancel
```

```
   if(cancel) then begin
     !error=envi_cancel_val()
     goto, trouble
   endif
  maxb(j)=0
 print, 'j',j
;stop
 if(j EQ 0) then begin
          newpos=[0]
  endif else begin
          newpos=intarr(j+1)
   for_now=where(mband NE 0)
   newpos(0:j-1)=mband(for_now)-1
  endelse

  for k=0,nb-1 do begin
   ; Rule out bands already included
   z=where(mband EQ pos(k)+1)
   if(z(0) eq (-1)) then begin
     newpos(j)=pos(k)

     ;Calculate B-dist for all class combinations
     for r=0,numclass-1 do begin
       for s=0,numclass-1 do begin

         new_size=size(newpos)
   ; Form class matrices and calculate class statistics
   roi_addr_1=envi_get_roi(roi_ids(r), roi_name=name, roi_color=color)
   roi_addr_2=envi_get_roi(roi_ids(s), roi_name=name, roi_color=color)

   if(j EQ 0) then begin
     class1=dblarr(n_elements(roi_addr_1), new_size(1))
     class1=envi_get_roi_data(roi_ids(r), fid=fid, pos=newpos)
     class2=dblarr(n_elements(roi_addr_2),new_size(1))
     class2=envi_get_roi_data(roi_ids(s), fid=fid, pos=newpos)
     amean=cl_mean(class1)
     bmean=cl_mean(class2)
     temp1=moment(class1)
     acov=temp1(1)
     temp2=moment(class2)
     bcov=temp2(1)
     icov=1./((acov+bcov)/2.)
     dcov=(acov+bcov)/2.
     t1cov=acov
     t2cov=bcov
     b1=1./8.*(amean-bmean)*icov*transpose(amean-bmean)
```

```
    ;help, b1
   endif else begin
    class1=dblarr(n_elements(roi_addr_1), new_size(1))
    class1=transpose(envi_get_roi_data(roi_ids(r), fid=fid, pos=newpos))
    ;help, class1
    class2=dblarr(n_elements(roi_addr_2),new_size(1))
    class2=transpose(envi_get_roi_data(roi_ids(s), fid=fid, pos=newpos))
    ;help, class2
    amean=cl_mean(class1)
    ;help, amean
    bmean=cl_mean(class2)
    ;help,bmean
    acov=cl_cov(class1)
    bcov=cl_cov(class2)
    icov=invert((acov+bcov)/2.)
    dcov=determ((acov+bcov)/2.)
    t1cov=determ(acov)
    t2cov=determ(bcov)
    b1=1/8.*transpose(amean-bmean)#icov#(amean-bmean)
    ;help, b1
   endelse

   ; Calculate Bhattacharyya distance
   B2=1./2.*alog(dcov/(sqrt(t1cov)*sqrt(t2cov)))
   B=B1+B2
  B_matrix(r,s)=B(0)
 endfor ; end s loop
endfor ; end r loop
;print, B_matrix
temp=total(B_matrix)
; Search for maximum B-distance
if(temp GT maxb(j))then begin
 maxb(j)=temp
 mband(j)=pos(k)+1
endif
;stop

endif
 endfor ; end of class loop (i)

endfor ;end of class loop(j)
!error=0
 trouble: if(!error NE 0) then envi_io_error, $
  'Forward Sequential Band Selection Processing', unit=unit
 envi_report_init, base=rbase, /finish
```

```
mband=mband-1
print, 'mband',mband
print, bnames(mband)
result=strarr(numbands)
result=bnames(mband)
if(in_memory) then mem_res=bnames(mband) $
 else writeu, unit, result
free_lun, unit

; Construct output widget
base=widget_base(title='Band Selection Output', /column, xsize=300)
quit=widget_button(base, value='Done', event_pro='quit_event')
list=widget_list(base, value=result, uvalue='list', ysize=numbands)
widget_control, base, /realize
xmanager, 'wlist', base

end
;***********************************************************************
pro fsbs, ev

widget_control, ev.id, get_uvalue=uvalue
if (uvalue eq 'sequential') then begin

 ; Get input file
 envi_select, title='Forward Sequential Band Selection Input File',$
  fid=fid, dims=dims, pos=pos, /mask, /roi

 if (fid eq -1) then return

 ; Widget for input parameters
 envi_center, xoff, yoff
 base=widget_auto_base(title='FSBS Input Parameters')
 sb=widget_base(base, /column, /frame)
 sb1=widget_base(sb, /row)

 wp=widget_param(sb1, prompt='Number of bands in spectral subset',$
  dt=2, xs=6, uvalue='numbands', ceil=n_elements(pos), $
  default=n_elements(pos)/2.0, /auto)

 sb=widget_base(base, /column, /frame)
 ofw=widget_outfm(sb, func='envi_out_check', uvalue='outf', /auto)
 ; Automanage the widget
 result=auto_wid_mng(base)
 if(result.accept eq 0) then return
 numbands=result.numbands
 print, numbands
```

```
  fsbs_doit, fid=fid, pos=pos, numbands=numbands, $
    out_name=result.outf.name, in_memory=result.outf.in_memory
endif
end
```

```
; SPECTRAL BASIS FUNCTIONS BAND SELECTOR - J. Laurenzano 1998
; The program is designed to select the statistically optimal
; user defined number of bands for a hyperspectral image where
; there are no gaps in the spectrum (ie the bands should occur
; at equal intervals across the input spectrum). The user is
; asked to input the input image file, spectral range minimum
; and maximum the increment separating adjacent bands, the number of
; bands which the program should average in the initial data reduction
; ( this value must be less than the total number of bands divided
; by the number of bands in the output subset), the number of bands
; in the output subset (should be less than 10), and the output file
; name.  The program will perform an initial basis function calculation.
; These basis functions will be displayed - the user will decide if
; another iteration is desired.  If another iteration is desired,
; the program will adjust the bands and re-calculate the basis
; functions.  This process continues until the user decides to stop.
; At that point the selected interval maxima and minima are
; displayed and saved to file.

;**********************************************************************
pro quit_event, event
  widget_control, event.top, /destroy
  return
end

;************************EVENT HANDLER*****************
pro sbf_doit_event, event

; Get the variable stored in the top level base user value
widget_control, event.top, get_uvalue=info, /no_copy

; determine which action caused the event
widget_control, event.id, get_uvalue=buttonvalue

; Proceed based on the button that was pushed
if buttonvalue EQ 'cancel' then begin
  widget_control, event.top, /destroy

info.selection(*,0)=info.bnames(info.int_min(info.interval-1))
info.selection(*,1)=info.bnames(info.int_max(info.interval-1))
info.swave(*,0)=info.wavelength(0,info.int_min(info.interval-1))
info.swave(*,1)=info.wavelength(1,info.int_max(info.interval-1))
print, 'result',info.selection
print, 'wavelength', info.swave

; **************** Error Computation *******************************
```

```
; Initialize tile
;tile_id=envi_init_tile(info.fid, info.pos, num_tiles=num_tiles, $
;  interleave=1)
;envi_report_setup, fname=info.fname, out_name=info.out_name, $
;  in_memory=0, title='Error Computation', base=rbase, /interupt
;envi_report_inc, rbase, num_tiles

;for i=0,num_tiles-1 do begin
;  sum_1=dblarr(info.ns,info.nb)
;  sum_2=dblarr(info.ns, info.nb)
;  sum_1a=dblarr(info.ns)
;  sum_2a=dblarr(info.ns)
;  sum_3=dblarr(info.ns)
;  envi_report_stat, rbase, i, num_tiles, cancel=cancel
;  if(cancel) then begin
;    !error=envi_cancel_val()
;    goto, trouble_4
;  endif
;  data=envi_get_tile(tile_id, i, ys=ys, ye=ye)
;  s_new=dblarr(info.ns, info.numbands)
;  for j=0, info.numbands-1 do begin
;    temp_a=dblarr(info.ns)
;    if (j EQ 0) then s_new(*,j)=info.s_temp(*,j,i) else begin
;      for k=0,j-1 do temp_a=temp_a+info.bij(j,k)*info.s_temp(*,k,i)
;    endelse
;    s_new(*,j)=info.s_temp(*,j,i)-temp_a
;  endfor
;  temp_b=dblarr(info.ns,info.nb)
;  for j=0,info.ns-1 do begin
;    for k=0,info.numbands-1 do $
;      temp_b(j,*)=temp_b(j,*)+s_new(j,k)*info.psi(k,*)
;  endfor
;  sum_1=(data-temp_b)^2
;  sum_2=(data)^2
;  for j=0,info.ns-1 do begin
;    sum_1a(j)=total(sum_1(j,*))
;    sum_2a(j)=total(sum_2(j,*))
;  endfor
;  sum_3=sum_1a/sum_2a
;  info.error=info.error+total(sum_3)
;endfor ; end i loop
;info.error=100*info.error
;print, 'error', info.error

;Process error message
;!error=0
```

```
;trouble_4: if(!error NE 0) then envi_io_error, 'SBF Processing',unit=unit
;Clean up Tile Pointer
;envi_tile_done, tile_id
;envi_report_init, base=rbase, /finish


;Allocate memory array or open output file
get_lun, unit
if(info.in_memory) then mem_res=strarr(info.numbands,2) $
 else openw, unit, info.out_name
; Store max and min values for selected bands
if(info.in_memory) then mem_res=info.selection $
 else printf, unit, info.selection
 free_lun, unit

 ; Create output widget list

 base=widget_base(title='Band Selection Output', /column, xsize=300)
 sb1=widget_base(base, /col, /frame)
 sb_1a=widget_base(sb1, /row)
 lab1=widget_label(sb_1a, value='Interval Minimum', xsize=30,$
  /align_center)
 lab2=widget_label(sb_1a, value='Interval Maximum', xsize=30, $
  /align_center)
 sb_1b=widget_base(sb1, /row)
 list1=widget_list(sb_1b, value=info.selection(0,*), $
  uvalue='list1', ysize=info.numbands, xsize=15)
 list1a=widget_list(sb_1b, value=info.swave(0,*), $
  uvalue='list1a', ysize=info.numbands, xsize=15)
 list2=widget_list(sb_1b, value=info.selection(1,*), $
  uvalue='list2', ysize=info.numbands, xsize=15)
 list2a=widget_list(sb_1b, value=info.swave(1,*), $
  uvalue='list2a', ysize=info.numbands, xsize=15)
 sb2=widget_base(base, /row, /frame)
 quit=widget_button(base, value='Done', event_pro='quit_event')
 widget_control, base, /realize
 xmanager, 'wlist', base
endif else begin


;******** Interval refinement*******************
 stop
 min_t=dblarr(info.num_intervals)
 max_t=dblarr(info.num_intervals)
 info.check=info.check+1
 for r=0,info.numbands-1 do begin
```

```
    value=info.interval(r)-1
    if(info.refine(r) eq 1) then begin
      if(info.int_min(value) LT info.nb-2) AND $
        (info.int_min(value) LE info.int_max(value)-2) then $
         min_t(value) = info.int_min(value)+1 else $
         min_t(value)=info.int_min(value)
       if(info.int_max(value) GT 0) AND $
         (info.int_max(value) GE info.int_min(value)+2) then $
         max_t(value)=info.int_max(value)-1 else $
         max_t(value)=info.int_max(value)
    endif else begin
    exam=max(info.psi(r,*))
    z=where(info.psi(r,*) EQ exam)
    print, 'z', z
    if (exam GT 0.85) then begin
    if(z(0) GE (2*r+1)*info.average/4) AND $
      (z(0) LE 3*(2*r+1)*info.average/4) then info.test=info.test+1 $
    else begin
     if (z(0) LT (2*r+1)*info.average/4) AND (info.int_min(value) GT 0)then $
       min_t(value)=info.int_min(value)-1
     if(z(0) GT 3*(2*r+1)*info.average/4) AND $
       (info.int_max(value) LT info.nb-1)then $
       max_t(value)=info.int_max(value)+1
     endelse
    endif else begin
      if (info.int_min(value) GT 0) then  $
        min_t(value)=info.int_min(value)-1
      if (info.int_max(value) LT info.nb-1) then $
        max_t(value)=info.int_max(value)+1 $
        else max_t(value)=info.int_max(value)
   endelse
  endelse
  endfor
  print, 'min', min_t
  print,'max', max_t
;
;***Repeat basis function computation****

   ; Definitions
x_si=dblarr(info.numbands, info.nb)
si_sj=dblarr(info.numbands, info.numbands)
psi_temp=dblarr(info.numbands, info.nb)

; Initialize data tiles using BIL format
tile_id=envi_init_tile(info.fid, info.pos, num_tiles=num_tiles, $
 interleave=1)
```

```
print, 'num_tiles', num_tiles

; Setup processing  status report
envi_report_setup, fname=info.fname, out_name=info.out_name, $
  in_memory=0, title='Basis Function Calculation', base=rbase, $
   /interupt
envi_report_inc, rbase, num_tiles
info.s_temp=dblarr(info.ns, info.numbands)
for i=0, num_tiles-1 do begin
  envi_report_stat, rbase, i, num_tiles, cancel=cancel
  if(cancel) then begin
   !error=envi_cancel_val()
   goto, trouble_2
  endif

  data=envi_get_tile(tile_id, i, ys=ys, ye=ye)

  for j=0, info.ns-1 do begin
   for k=0, info.numbands-1 do begin
   ;print, 'k',k
   ;print, 'numint', num_intervals
    value=info.interval(k)-1 ;**compensate for added 1
                                                            ; in previous section
    info.s_temp(j,k)=total(data(j,min_t(value):max_t(value)))/ $
        (info.wavelength(max_t(value))-info.wavelength(min_t(value)))
   endfor
  endfor

  for l=0,info.nb-1 do begin
   for j=0,info.numbands-1 do begin
     x_si(j,l)=x_si(j,l)+total(data(*,l)*info.s_temp(*,j))
        for k=0,info.numbands-1 do begin
     si_sj(j,k)=si_sj(j,k) + total(info.s_temp(*,j)*info.s_temp(*,k))
     ;print, 'sij',si_sj(j,k)
    endfor
   endfor
  endfor

endfor
x_si = (x_si)/(info.ns*info.nl)
si_sj=(si_sj)/(info.ns*info.nl)

;delvar, data, info.s_temp

; Process error messages
!error=0
```

```
trouble_2: if(!error NE 0) then envi_io_error, 'SBF Processing', unit=unit
; Clean up tile pointer
envi_tile_done, tile_id
envi_report_init, base=rbase, /finish

; Compute Basis Function
dij=dblarr(info.numbands, info.numbands)
dij(0,0)=1
info.bij=dblarr(info.numbands, info.numbands)
pij=dblarr(info.numbands, info.numbands)

psi_temp(0,*) = x_si(0,*)/si_sj(0,0)
new_test=max(psi_temp(0,*))
if (info.check GE 1) AND (new_test LT max(info.psi(0,*))) then $
   info.refine(0)=1 else begin
   info.psi(0,*)=psi_temp(0,*)
   info.int_min(info.interval(0)-1)=min_t(info.interval(0)-1)
   info.int_max(info.interval(0)-1)=max_t(info.interval(0)-1)
endelse


for i=1,info.numbands-1 do begin
 value=info.interval(i)-1
 ; Compute bij
 for j=0,i-1 do begin
  info.bij(i,j)= total(info.psi(j,min_t(value):max_t(value)))/ $
   (info.wavelength(max_t(value))-info.wavelength(min_t(value)))
 endfor
 ; Compute dij
 for j=0,i do begin
  if(j EQ i) then dij(i,j)=1 else $
   for k=j,i-1 do  dij(i,j)=dij(i,j)+info.bij(i,k)*dij(k,j)
  ; Compute Pij
  for k=0,i do begin
   for l=0,i do begin
    pij(i,j)=pij(i,j)+dij(i,k)*dij(j,l)*si_sj(k,l)
   endfor
  endfor
 endfor
 sum_b=dblarr(info.nb)
 sum_a=dblarr(info.nb)
 for j=0,i do sum_a=sum_a+dij(i,j)*x_si(j,*)
 for j=0,i-1 do sum_b=sum_b+pij(i,j)*psi_temp(j,*)
 psi_temp(i,*)=(sum_a - sum_b)/pij(i,i)
 print, 'psi_temp', psi_temp(i,*)
 new_test=max(psi_temp(i,*))
```

```
  if (info.check GE 1) AND (new_test LT max(info.psi(i,*))) then $
   info.refine(i)=1 else begin
   info.psi(i,*)=psi_temp(i,*)
   info.int_min(value)=min_t(value)
   info.int_max(value)=max_t(value)
  endelse
 endfor ; end i loop
 print, 'min', info.int_min
 print, 'max', info.int_max
 print, 'bij',info.bij
 print, 'dij', dij
 print, 'pij', pij
 print, 'psi', info.psi
 ; Update User Query Widget
 widget_control, info.list, set_value=info.psi

 ; return the info variable to the top level base
 widget_control, event.top, set_uvalue=info, /no_copy

 endelse
 end

;***************************************************************************
;*****************MAIN PROGRAM*******************************************
pro sbf_doit, fid=fid, pos=pos, dims=dims, init_interval=init_interval,$
   file=file, average=average, numbands=numbands, $
   out_name=out_name, in_memory=in_memory, r_fid=r_fid

envi_file_query, fid, fname=fname, nb=nb, ns=ns, nl=nl, $
  bnames=bnames, xstart=xstart, ystart=ystart


;*********INTERVAL SELECTION******************************************

; Read spectral band information file into array
wavelength=fltarr(init_interval,2)
get_lun, lun
openr, lun, file
readf, lun, wavelength
free_lun, lun
print, 'wavelength', wavelength
print, 'yet another testing new file'
; Initialize data tiles using BIL format
tile_id=envi_init_tile(fid, pos, num_tiles=num_tiles, interleave=1)
print, 'num_tiles', num_tiles
```

```
; Setup processing status report
envi_report_setup, fname=fname, out_name=out_name, $
 in_memory=0, title='Interval Selection', base=rbase, $
 /interupt
envi_report_inc, rbase, num_tiles

; Definitions
sp_min=wavelength(0,*)
sp_max=wavelength(1,*)
test=init_interval mod average
if (test eq 0) then begin
  num_intervals=init_interval/average
endif else num_intervals= fix(init_interval/average +1)
x_ave=dblarr(ns, nl, num_intervals)


for i=0, num_tiles-1 do begin
  envi_report_stat, rbase, i, num_tiles, cancel=cancel
  if(cancel) then begin
    !error=envi_cancel_val()
    goto, trouble
  endif

 ; Retrieve tile data - each tile represents each pixel of
 ; one line in all bands
 data=envi_get_tile(tile_id, i, ys=ys, ye=ye)
 ;help, data
 temp_1=size(data)

 x_temp=dblarr(ns, num_intervals)
 int_min=dblarr(num_intervals) ; array address of interval
 int_max=dblarr(num_intervals) ; min and max wavelengths
 for j=0, temp_1(1)-1 do begin
   for k=0, num_intervals-2 do begin
   int_min(k)=k*average
   int_max(k)=(k+1)*average-1
     x_temp(j,k)=total(data(j,int_min(k):int_max(k)))
   endfor
   int_min(num_intervals-1)=(num_intervals-1)*average
   int_max(num_intervals-1)=nb-1
   x_temp(j,num_intervals-1)= $
     total(data(j,int_min(num_intervals-1):int_max(num_intervals-1)))
 endfor
 ;print, 'xtemp',x_temp
 x_ave(*,i,*)=x_temp
endfor
```

```
print, 'min', int_min
print, 'max', int_max

;Process error message
!error=0
trouble: if(!error NE 0) then envi_io_error, 'SBF Processing', unit=unit
; Clean up tile pointer
envi_tile_done, tile_id
envi_report_init, base=rbase, /finish
interval=intarr(numbands)
; Rule out bands already included and compute residual
for m=0,numbands-1 do begin
 print, 'm', m
 print, 'numintervals', num_intervals

 res_init=dblarr(num_intervals)
 for i=0,num_intervals-1 do begin
  x_h=dblarr(ns,nl)
  z=where(interval EQ i+1)
  if(z(0) EQ -1) then begin
   x_h=x_ave(*,*,i)
   sum_2=dblarr(num_intervals)
   sum_3=dblarr(num_intervals)
   for j=0, num_intervals-1 do begin
    q=where(interval EQ j+1)
    if(q(0) EQ -1) AND (j NE i) then begin
     sum_2(j)=(total((x_ave(*,*,j))*x_h))^2
     ;print, 'sum2', sum_2
     sum_3(j)=total(x_h^2)
     ;print, 'sum3', sum_3
    endif
   endfor

   a=where(sum_3 NE 0)
   if (a(0) EQ -1) then res_init(i)=0 $
    else res_init(i)=total(sum_2(a)/sum_3(a))
  endif else res_init(i)=0
 ;print, 'res', res_init(i)
endfor

print, 'min',min(res_init(where(res_init NE 0)))
b=min(res_init(where(res_init NE 0)))
;print, 'b', b
b1=where(res_init EQ b)
;print, b1, b1
interval(m)=b1 + 1;**Remember the added 1**
```

```
 endfor
 print, 'interval', interval

 ;delvar, x_h, sum_1, sum_2, x_ave, x_temp, data

;****************Calculate Basis Function****************************

; Definitions
x_si=dblarr(numbands, nb)
si_sj=dblarr(numbands, numbands)
psi=dblarr(numbands, nb)

; Initialize data tiles using BIL format
tile_id=envi_init_tile(fid, pos, num_tiles=num_tiles, interleave=1)
print, 'num_tiles', num_tiles

; Setup processing  status report
envi_report_setup, fname=fname, out_name=out_name, $
 in_memory=0, title='Basis Function Calculation', base=rbase, $
  /interupt
envi_report_inc, rbase, num_tiles
s_temp=dblarr(ns, numbands)
for i=0, num_tiles-1 do begin

 envi_report_stat, rbase, i, num_tiles, cancel=cancel
 if(cancel) then begin
  !error=envi_cancel_val()
  goto, trouble_1
 endif

 data=envi_get_tile(tile_id, i, ys=ys, ye=ye)

 for j=0, ns-1 do begin
  for k=0, numbands-1 do begin
  ;print, 'k',k
  ;print, 'numint', num_intervals
   value=interval(k)-1 ;**compensate for added 1 in previous section
   s_temp(j,k)=(total(data(j,int_min(value):int_max(value))))/ $
    (wavelength(int_max(value))-wavelength(int_min(value)))
  endfor
 endfor

 for l=0,nb-1 do begin
  for j=0,numbands-1 do begin
   x_si(j,l)=x_si(j,l) + total(data(*,l)*s_temp(*,j))
   for k=0,numbands-1 do begin
```

```
      si_sj(j,k)=si_sj(j,k) + total(s_temp(*,j)*s_temp(*,k))
      ;print, 'sij',si_sj(j,k)
     endfor
   endfor
  endfor

 endfor
 x_si=(x_si)/(ns*nl)
 si_sj=(si_sj)/(ns*nl)

 ; Process error messages
 !error=0
 trouble_1: if(!error NE 0) then envi_io_error, 'SBF Processing', unit=unit
  ;Clean up tile pointer
 envi_tile_done, tile_id
 envi_report_init, base=rbase, /finish

 ; Compute Basis Function
 dij=dblarr(numbands, numbands)
 bij=dblarr(numbands, numbands)
 pij=dblarr(numbands, numbands)
 dij(0,0)=1
 pij(0,0)=si_sj(0,0)
 psi(0,*) = x_si(0,*)/si_sj(0,0)

 for i=1,numbands-1 do begin
  value=interval(i)-1
  ; Compute bij
  for j=0,i-1 do begin
   bij(i,j)= total(psi(j,int_min(value):int_max(value)))/ $
    (wavelength(int_max(value))-wavelength(int_min(value)))
   endfor
   ; Compute dij
   for j=0,i do begin
    if(j EQ i) then dij(i,j)=1 else begin
     for k=j,i-1 do  dij(i,j)=dij(i,j)+bij(i,k)*dij(k,j)
     dij(i,j)=-dij(i,j)
    endelse
    ; Compute Pij
    for k=0,i do begin
     for l=0,i do begin
      pij(i,j)=pij(i,j)+dij(i,k)*dij(j,l)*si_sj(k,l)
     endfor
    endfor
   endfor
   sum_b=dblarr(nb)
```

```
  sum_a=dblarr(nb)
  for j=0,i do sum_a=sum_a+dij(i,j)*x_si(j,*)
  for j=0,i-1 do sum_b=sum_b+pij(i,j)*psi(j,*)
  psi(i,*)=(sum_a - sum_b)/pij(i,i)
endfor ; end i loop
;print, 'bij',bij
;print, 'dij', dij
;print, 'pij', pij
;print, 'psi', psi

;delvar, s_temp, data, x_si, si_sj

; Display PSI and Query user for continuation
; Create User Interface

first= 'Press OK to continue. Press Cancel to end calculations.'
result=bnames(interval-1)
envi_center,xoff,yoff
base=widget_base(/col, /frame, xoff=xoff, yoff=yoff, $
  title='First Iteration Basis Functions')
sbase1=widget_base(base, /col)
if (nb LT 20) then n_size=nb else n_size=20
list_1=widget_table(sbase1, xsize=numbands, ysize=n_size, value=psi)
sbase2=widget_base(base, /col)
lab1=widget_label(sbase2, value=first, /align_center)
sbase3=widget_base(base, /frame, /row)
c_button=widget_button(sbase3, value='Cancel', uvalue='cancel')
ok_button=widget_button(sbase3, value='OK', uvalue='ok')

; Save information that must be passed between the main procedure
; and the event handler

count=intarr(numbands)
refine=intarr(numbands)
selection=strarr(numbands, 2)
swave=fltarr(numbands,2)
test=0
check=0
error=0
s_temp=dblarr(ns,numbands)
bij=dblarr(numbands, numbands)

info={fid:fid, ns:ns,nl:nl, nb:nb, sp_min:sp_min, sp_max:sp_max,$
 average:average, numbands:numbands, psi:psi, $
 out_name:out_name, in_memory:in_memory, bnames:bnames, interval:interval, $
 wavelength:wavelength, pos:pos, fname:fname, list:list_1, test:test, $
```

```
 count:count, check:check, refine:refine, selection:selection, $
 error:error, num_intervals:num_intervals,int_min:int_min, $
 int_max:int_max, s_temp:s_temp, bij:bij,swave:swave }

widget_control, base, set_uvalue=info, /no_copy
; Realize the GUI and start the Xmanager loop
widget_control, base, /realize
xmanager, 'sbf_doit', base, event_handler='sbf_doit_event'

end


;**********************************************************************
pro sbf, ev

widget_control, ev.id, get_uvalue=uvalue
if(uvalue eq 'basis') then begin
 ; get input file
 envi_select, title='Spectral Basis Function Input File', fid=fid, $
   dims=dims, pos=pos, /mask, /roi
 if (fid eq -1) then return

 ; Widget for input parameters
 envi_center, xoff, yoff
 base=widget_auto_base(title='Spectral Basis Function Input Parameters')
 top=widget_base(base, /row)
 sb=widget_base(top, /column, /frame)
 sb1=widget_base(sb, /colum)
 wp=widget_param(sb1, prompt='Number of Bands in Image', dt=4, xs=6, $
  uvalue='init_interval', /auto)
 sb1=widget_base(sb, /colum)
 lab=widget_slabel(sb1, prompt='Enter the spectral band information file name',$
   xsize=30,  /frame)
 input=widget_string(sb1, uvalue='file', /auto)
 sb1=widget_base(sb, /column)
 wp=widget_param(sb1, prompt='Spectral range averaging number', $
  dt=4, xs=6, uvalue='average', /auto)
 sb1=widget_base(sb, /column)
 wp=widget_param(sb1, prompt='Number of bands in spectral subset',$
 dt=4, xs=6, uvalue='numbands', /auto)
 sb=widget_base(top, /column, /frame)
 ofw=widget_outfm(sb, func='envi_out_check', uvalue='outf', /auto)
 ; Automanage the widget
 result=auto_wid_mng(base)
 if(result.accept eq 0) then return
```

```
  init_interval=result.init_interval
  file=result.file
  average=result.average
  numbands=result.numbands
  sbf_doit, fid=fid, pos=pos, dims=dims, init_interval=init_interval,$
   file=file, average=average, numbands=numbands, $
   out_name=result.outf.name, in_memory=result.outf.in_memory
endif

end
```

```
; ENVI/IDL EIGENVECTOR PRE-SELECTION METHOD - J. Laurenzano (1997)

; PRESC inputs training class samples and the number of bands
; in the desired output subset.  The eigenvalues and eigenvectors
; of the pooled covariance matrix are determined where pooled refers
; to the sum of the individual class covariance matrices.  The
; band names for the optimal spectral subset are output
;*********************************************************************
pro quit_event, event
 widget_control, event.top, /destroy
end

pro presc_do, fid=fid,pos=pos, dims=dims,out_name=out_name,$
 numbands=numbands,in_memory=in_memory, r_fid=r_fid

; Initialize optional keywords
;!error=0
;on_ioerror, trouble
;in_memory=keyword_set(in_memory)

envi_file_query,fid, fname=fname,nb=nb, ns=ns,nl=nl, $
 bnames=bnames, xstart=xstart, ystart=ystart

; Allocate memory array or open output file
get_lun, unit
if(in_memory) then mem_res=strarr(numbands)$
 else openw, unit, out_name

roi_ids=envi_get_roi_ids(fid=fid)
; Establish Status Bar
envi_report_setup, fname=fname, out_name=out_name, $
 in_memory=0, title='Eigenvector Pre-Selection', $
 base=rbase, /interupt
envi_report_inc, rbase, n_elements(roi_ids)
; Calculate pooled covariance matrix
pool=dblarr(nb,nb) ; Define pooled covariance matrix
 for i=0, n_elements(roi_ids)-1 do begin
  envi_report_stat, rbase, i, n_elements(roi_ids), $
   cancel=cancel
  if(cancel) then begin
   !error=envi_cancel_val()
   goto, trouble
  endif
  roi_addr=envi_get_roi(roi_ids(i),roi_name=name, roi_color=color)
  cl_matrix=dblarr(n_elements(roi_addr),nb)
  for j=0,nb-1 do begin    ; fill class matrix
```

```
    cl_matrix(*,j)=envi_get_roi_data(roi_ids(i),fid=fid,pos=pos(j))
   endfor
   pool=pool+cl_cov(cl_matrix)
   ;result=envi_get_roi_data(roi_ids(i),fid=fid,pos=pos(1))
   help, pool
  endfor

  !error=0
  trouble: if(!error NE 0) then envi_io_error, $
   'Eigenvector Pre-Selection Processing', unit=unit
  envi_report_init, base=rbase, /finish

; Calculate eigenvalues and eigenvectors of pooled cov matrix
eval=hqr(elmhes(pool), /double)
residual=1
evec=eigenvec(pool,eval, residual=residual)
help, evec
;print, 'evec',evec

; Select the best M spectral bands from the entire set-
; inspect the first M eigenvectors for the band with the highest
; positive or negative loading in each eigenvector
spmax=dblarr(numbands)
for i=0,numbands-1 do begin
  temp=dblarr(nb)
  temp=evec(*,i)
  temp=sqrt(temp^2)
  count_2=0
  order=reverse(sort(temp))
  while(spmax(i) eq 0) do begin
   a_test=where(spmax eq order(count_2)+1 )
   print, 'test',a_test
   if(a_test(0) eq -1) then spmax(i)=order(count_2)+ 1 $
    else count_2=count_2+1
   print, 'count', count_2
  endwhile
endfor
spmax=spmax-1
print, spmax
print, bnames(spmax)
;print, pos(spmax)
result=bnames(spmax)

; Output data
if(in_memory) then mem_res=bnames(spmax) $
 else printf, unit, bnames(spmax)
```

```
free_lun, unit

; Create output widget list
base=widget_base(title='Band Selection Output', /column, xsize=300)
quit=widget_button(base, value='Done', event_pro='quit_event')
list=widget_list(base, value=result, uvalue='list', ysize=numbands)
widget_control, base, /realize
xmanager, 'wlist', base

end
;***************************************************************************
pro presc, ev

widget_control, ev.id, get_uvalue=uvalue
if (uvalue eq 'prescreen') then begin

 ; get input file
 envi_select, title='Pre-Screen Input File', fid=fid, dims=dims, $
         pos=pos, /mask, /roi
 if (fid eq -1) then return

 ; Widget for input parameters
 envi_center,xoff,yoff
 base=widget_auto_base(title='Pre-Screen Input Parameters')
 sb=widget_base(base,/column,/frame)
 sb1=widget_base(sb,/row)
 wp=widget_param(sb1,prompt='Number of bands in spectral subset', $
  dt=2, xs=6,uvalue='numbands', ceil=n_elements(pos), $
  default=n_elements(pos)/2.0, /auto)
 sb=widget_base(base,/column,/frame)
 ofw=widget_outfm(sb,func='envi_out_check', $
  uvalue='outf',/auto)
 ;Automanage the widget
 result=auto_wid_mng(base)
 if (result.accept eq 0) then return
 numbands=result.numbands
 ;print, numbands
 presc_do, fid=fid,pos=pos,dims=dims,numbands=numbands,$
  out_name=result.outf.name, in_memory=result.outf.in_memory
endif
 end
```

; **ENVI/IDL SIGNAL-TO-CLUTTER RATIO CLASSIFIER** - J. Laurenzano (1997)

; This classifier is intended for use with target/background imagery.
; Target and background class training samples are input. A classified
; image is output.

```
;************************************************************************

pro scr1_doit, fid=fid,pos=pos,dims=dims,out_name=out_name, $
  numbands=numbands, in_memory=in_memory, r_fid=r_fid, $
  target=target, thold=thold

envi_file_query, fid, fname=fname, nb=nb, ns=ns, nl=nl, $
  bnames=bnames, xstart=xstart, ystart=ystart, interleave=interleave, $
  data_type=data_type
print, 'data type', data_type

tile_interleave=interleave
temp=size(pos)
nb=temp(1)

; Allocate memory array or open output file

get_lun, unit
if(in_memory) then mem_res=dblarr(ns,nl) $
  else openw, unit, out_name

; Calculate class covariance matrix
roi_ids=envi_get_roi_ids(fid=fid)
num_class=n_elements(roi_ids)
cov_matrix=dblarr(nb,nb,num_class)
tempa=size(bnames)
name_type=tempa(2)
cl_names=make_array(n_elements(roi_ids), type=name_type)
cl_color=lonarr(3,num_class)

for i=0,num_class-1 do begin
 roi_addr=envi_get_roi(roi_ids(i), roi_name=name, roi_color=color)
 cl_matrix=dblarr(n_elements(roi_addr), nb)
 cl_names(i)=name
 cl_color(*,i)=color
 for j=0, nb-1 do begin
  cl_matrix(*,j)=envi_get_roi_data(roi_ids(i), fid=fid, pos=pos(j))
 endfor
```

```
 ; Fill covariance matrix
 cov_matrix(*,*,i)=cl_cov(cl_matrix)
endfor

; Assign target and background class positions

if( target eq 1) then  begin
 t=0
 b=1
endif else begin
 t=1
 b=0
endelse

; Initialize the data tiles using BIP format
tile_id=envi_init_tile(fid, pos, num_tiles=num_tiles, interleave=1)
print, 'numtiles', num_tiles

;Setup processing status report
envi_report_setup, fname=fname, out_name=out_name, $
 in_memory=0, title='Signal to Clutter Classifier', base=rbase, $
 /interupt
envi_report_inc, rbase, num_tiles

sig=dblarr(ns,nl)

for i=0, num_tiles-1 do begin
 envi_report_stat, rbase, i, num_tiles, cancel=cancel
 if(cancel) then begin
 !error=envi_cancel_val()
 goto, trouble
 endif

 ; Retrieve tile data - each tile represents each pixel of
 ; one line in all bands

 data=envi_get_tile(tile_id, i, ys=ys, ye=ye)
 temp=size(data)


 ; Calculate SCR
 ; Select each image pixel

 for r=0, temp(1)-1 do begin
  pixel=dblarr(temp(2))
  pixel=data(r,*)
```

```
    sig(r,i)=pixel#invert(cov_matrix(*,*,b))# transpose(pixel)
  endfor  ; end r-loop

 endfor  ; end i-loop

 result=fltarr(ns,nl)

 threshold=thold*max(sig)
 back=where(sig LT threshold)
 tg=where(sig GE threshold)

 if(back(0) eq -1) then begin
  result=result+t
  print, 'no background', r
 endif

 if(tg(0) eq -1) then begin
  result=result+b
  print, 'no target',r
 endif

 if (back(0) ne -1) and (tg(0) ne -1) then begin
    print, 'num bg', n_elements(back)
    print, 'num target', n_elements(tg)
    print, 'total', n_elements(back)+n_elements(tg)
    result(back)=result(back)+b
    result(tg)=result(tg)+t
  endif

; Write output to memory or output file
  if(in_memory) then mem_res=result $
    else writeu, unit, result

; Process error messages
!error=0
trouble: if(!error NE 0) then envi_io_error, 'SCR Processing', $
  unit=unit
free_lun, unit

; Clean up tile pointer
envi_tile_done, tile_id
envi_report_init, base=rbase, /finish

if(!error EQ 0) then begin
  ;Add the processed file to the available band list, the output
  ; file will inherit the wavelength and band information from the input file
```

```
 inherit={fid:fid, pos:pos, flag:3}
 descrip='SCR Classification'
if(in_memory) then $
 envi_enter_data, mem_res, descrip=descrip, r_fid=r_fid, $
    inherit=inherit, num_classes=num_class, class_names=cl_names, $
    lookup=cl_color, bnames='SCR' $
else $
 envi_setup_head, fname=out_name, ns=ns, nl=nl, nb=1, $
  r_fid=r_fid, inherit=inherit, descrip=descrip, xstart=xstart, $
  ystart=ystart,  $
  lookup=cl_color, data_type=data_type, $
  interleave=0,bnames=out_name,/write, /open
 endif

end
;***************************************************************************
pro scr1, ev

widget_control, ev.id, get_uvalue=uvalue
if(uvalue eq 'scr1') then begin
 ; Get input file
 envi_select, title='SCR Input File', fid=fid, dims=dims, pos=pos, $
  /mask, /roi

 if(fid eq -1) then return

 ; Widget input parameters
 envi_center, xoff, yoff
 base=widget_auto_base(title='SCR Input Parameters')
 sb=widget_base(base, /column, /frame)
 sb1=widget_base(sb, /col)
 wp=widget_param(sb1, prompt='Region of Target Class Representation', $
  uvalue='target', default=1, /auto)
 sb1=widget_base(sb, /col)
 wp=widget_param(sb1, prompt='Threshold (percentage of maximum value)', $
  uvalue='thold', default=0.75, /auto)
 sb1=widget_base(sb, /col)

 ofw=widget_outfm(sb1, func='envi_out_check', uvalue='outf', /auto)

 ; Automanage the widget
 result=auto_wid_mng(base)
 if(result.accept eq 0) then return
 target=result.target
 thold=result.thold
```

```
 scr1_doit, fid=fid, pos=pos, dims=dims, out_name=result.outf.name, $
  in_memory=result.outf.in_memory, target=target, thold=thold
endif

end
```

; **ENVI/IDL LOG-LIKELIHOOD RATIO CLASSIFIER** - J. Laurenzano (1997)

```
; This classifier is intended for use with target/background images.
; Target and background class training samples are input in addition
; to both target and background class probabilities.  A classified
; image is output.

;*******************************************************************

pro log_doit, fid=fid,pos=pos, dims=dims,out_name=out_name, $
 numbands=numbands,in_memory=in_memory, r_fid=r_fid, $
 tprob=tprob, bprob=bprob, target=target

envi_file_query,fid,fname=fname,nb=nb,ns=ns,nl=nl,$
 bnames=bnames,xstart=xstart,ystart=ystart, interleave=interleave,$
 data_type=data_type


tile_interleave=interleave
temp=size(pos)
nb=temp(1)

;Allocate memory array or open output file
get_lun,unit
if(in_memory) then mem_res=dblarr(ns,nl) $
 else openw,unit,out_name, /block

; Calculate class covariance matrix
roi_ids=envi_get_roi_ids(fid=fid)
num_class=n_elements(roi_ids)
cov_matrix=dblarr(nb,nb,num_class)
mean_matrix=dblarr(nb, num_class)
tempa=size(bnames) ; Form array containing class names
name_type=tempa(2)
cl_names=make_array(n_elements(roi_ids), type=name_type)
cl_color=lonarr(3,num_class)

for i=0,num_class-1 do begin
 roi_addr=envi_get_roi(roi_ids(i), roi_name=name, roi_color=color)
 cl_matrix=dblarr(n_elements(roi_addr), nb)
 cl_names(i)=name
 cl_color(*,i)=color
 for j=0, nb-1 do begin  ; Fill class matrix
  cl_matrix(*,j) = envi_get_roi_data(roi_ids(i), fid=fid, pos=pos(j))
 endfor
 ; Fill covariance matrix
```

```
  cov_matrix(*,*,i)=cl_cov(cl_matrix)
  mean_matrix(*,i)=cl_mean(cl_matrix)
endfor
help, cov_matrix
print, cl_names
print, cl_color
print, 'mean', mean_matrix
; Assign target and background class positions
if(target EQ 1) then begin
 t=0
 b=1
endif else begin
 t=1
 b=0
endelse

;Initialize the data tiles using BIP format
tile_id=envi_init_tile(fid,pos, num_tiles=num_tiles, interleave=1)
print, 'interleave', interleave
print, 'num_tiles', num_tiles

; Setup the processing status report
envi_report_setup, fname=fname, out_name=out_name, $
 in_memory=0, title='Log-Likelihood Ratio Classifier', base=rbase, $
 /interupt
envi_report_inc, rbase, num_tiles

for i=0, num_tiles-1 do begin
  envi_report_stat, rbase, i, num_tiles, cancel=cancel
 if (cancel) then begin
   !error=envi_cancel_val()
   goto, trouble
 endif

 ; Retrieve tile data - each tile represents each pixel of
 ; one line in all bands
 data=envi_get_tile(tile_id, i, ys=ys, ye=ye)
 temp=size(data)
 result=dblarr(temp(1))
 ; Calculate Log-Likelihood
 ratio=alog(tprob/bprob)-1/2.* $
  alog(determ(cov_matrix(*,*,b))/determ(cov_matrix(*,*,t)))
 ; Select each image pixel
 for r=0, temp(1)-1 do begin
  pixel=dblarr(temp(2))
  pixel=data(r,*)
```

```
    sum=(1/2.)*(pixel-mean_matrix(*,b))# $
     invert(cov_matrix(*,*,b))# (transpose(pixel-mean_matrix(*,b))) - $
     (1/2.) *(pixel-mean_matrix(*,t)) # $
     invert(cov_matrix(*,*,t))# (transpose(pixel-mean_matrix(*,t)))

    if(sum(0) GT ratio) then result(r)=t else result(r)=b


   ; Write output to memory or output file
  endfor ; End r loop
  if(in_memory) then mem_res(*,i)=result $
    else writeu, unit, result
endfor ; End i loop (tile loop)

;Process error message
!error=0
trouble: if(!error NE 0) then envi_io_error,'Log-likelihood Processing',$
  unit=unit
free_lun, unit
if(!error EQ 0) then begin
  ; Add the processed file to the available band list, the output
  ; file will inherit the wavelength and band information from
  ; the input file
  inherit={fid:fid, pos:pos, flag:3}
  descrip='Log-Likelihood Classification'
  if (in_memory) then $
    envi_enter_data, mem_res, descrip=descrip, r_fid=r_fid, $
      inherit=inherit, num_classes=num_class, class_names=cl_names, $
      lookup=cl_color $
  else envi_setup_head, fname=out_name, ns=ns, nl=nl, nb=1, $
    r_fid=r_fid, inherit=inherit, descrip=descrip, xstart=xstart, $
    ystart=ystart, num_classes=num_class, class_names=cl_names, $
    lookup=cl_color, /write, /open
endif

; Clean up tile pointer
envi_tile_done, tile_id
envi_report_init, base=rbase, /finish


end

;*************************************************************************
pro log, ev
widget_control, ev.id, get_uvalue=uvalue
if(uvalue eq 'log') then begin
```

```
; Get input file
envi_select, title='Log-Likelihood Input', fid=fid, dims=dims, pos=pos, $
 /mask, /roi

if(fid eq -1) then return

;Widget input parameters
envi_center,xoff,yoff
base=widget_auto_base(title='Log-Likelihood Input Parameters')
sb=widgct_basc(basc,/column,/framc)
sb1=widget_base(sb, /column)
wp=widget_param(sb1, prompt='Probability of Target Class', $
 dt=4, xs=6, uvalue='tprob', default=0.5, /auto)
sb1=widget_base(sb, /column)
wp=widget param(sb1, prompt='Region of Target Class Representation',$
  uvalue='target', default= 1, /auto)
sb1=widget_base(sb, /column)
wp=widget_param(sb1, prompt='Probability of Background Class', $
 dt=4, xs=6, uvalue='bprob', default=0.5, /auto)
sb=widget_base(sb, /column, /frame)
ofw=widgct_outfm(sb,func='cnvi_out_chcck',uvaluc='outf',/auto)
; Automanage the widget
result=auto_wid_mng(base)
if(result.accept EQ 0) then return
target=result.target
tprob=result.tprob
bprob=result.bprob
log_doit, fid=fid, pos=pos, dims=dims, out_name=result.outf.name, $
 in_memory=result.outf.in_memory, tprob=tprob, bprob=bprob, $
 target=target
endif

end
```

```
; INDEPENDENT ANALYSIS CONFUSION MATRIX - J. Laurenzano, 1997

; This program was developed to produce a confusion matrix
; based on independent sampling techniques. The ROI file used
; for classification should be renamed and a new ROI file
; specifically intended for the accuracy assessment must be
; created. The first input image should be the original image with
; which the new ROI data is associated. The second input image should be
; the class map image. The program will print out a labeled confusion
; matrix in the IDL window. If selected, the program will also output
; the confusion matrix and class names into an output file named
; by the user.

; **********************Main Program*******************************

pro conf_doit, fid_1=fid_1, fid_2=fid_2, pos_1=pos_1, pos_2=pos_2, $
dims_1=dims_1, dims_2=dims_2, out_name=out_name, $
 in_memory=in_memory, r_fid_1=r_fid_1, r_fid_2=r_fid_2

; Allocate memory array or open output file
;get_lun, unit
;if(in_memory) then mem_res=intarr(numclass, numclass+1) $
;  else openw, unit, out_name


print, 'fid2', fid_2
print, 'fid1', fid_1

; Gather image data
envi_file_query, fid_1, fname=fname, nb=nb, ns=ns, nl=nl, $
 data_type=data_type, bnames=bnames
 ns_1=ns
 nl_1=nl
 bnames_1=bnames

 tempa=size(bnames_1)
 name_type=tempa(2)
print, 'ns_1', ns_1

envi_file_query, fid_2, fname=fname, nb=nb, ns=ns, nl=nl, $
 data_type=data_type
 ns_2=ns
 nl_2=nl
 print, 'ns_2', ns_2

; Retrieve classified image pixel values
```

```
tile_id=envi_init_tile(fid_2, pos_2, num_tiles=num_tiles, interleave=0)
 print, 'num_tiles', num_tiles

data=intarr(ns_2,nl_2)

for i=0, num_tiles-1 do begin
  data(*,i*nl_2/num_tiles:(i+1)*nl_2/num_tiles-1)=$
    envi_get_tile(tile_id, i, ys=ys, ye=ye)
  print, 'values',max(data)
  print, 'values', min(data)
endfor

; Define confusion matrix
numclass=max(data)
c_mat=intarr(numclass, numclass+1)

; Allocate memory unit
get_lun, unit
if(in_memory) then mem_res=intarr(numclass,numclass+1) $
  else openw, unit, out_name

; Retrieve ROI information
roi_ids=envi_get_roi_ids(fid=fid_1)
cl_names=make_array(n_elements(roi_ids), type=name_type)
for i=0, n_elements(roi_ids)-1 do begin
  roi_addr=envi_get_roi(roi_ids(i), roi_color=color, roi_name=name)
  cl_names(i)=name
  ;print, n_elements(roi_addr)
  ;print, 'rois',roi_ids

  for j=0, n_elements(roi_addr)-1 do begin
    xloc=roi_addr(j) mod ns_2
    ;help, data
    ;print, 'x', xloc
    ;print, roi_addr(j)
    ;print, ns_2
    yloc=roi_addr(j)/ns_2
    ;print, yloc

    if(data(xloc, yloc) eq 0) then begin
      c_mat(i,numclass)=c_mat(i,numclass)+1
    endif else begin
           c_mat(i,data(xloc,yloc)-1)=c_mat(i,data(xloc,yloc)-1)+1
         endelse
  endfor
endfor
```

```
print, c_mat

; Store output confusion matrix
if(in_memory) then mem_res=c_mat $
 else printf, unit, c_mat
free_lun, unit

end

;****************************************************************
pro conf, ev
widget_control, ev.id, get_uvalue=uvalue
if(uvalue eq 'confusion') then begin
 envi_select, title='Independent Analysis Truth Image',$
  fid=fid, dims=dims, pos=pos, /mask, /roi
 fid_1=fid
 dims_1=dims
 pos_1=pos
 if(fid eq -1) then return
 envi_select, title='Independent Analysis Classified Image', $
  fid=fid, dims=dims, pos=pos, /mask, /roi
 fid_2=fid
 dims_2=dims
 pos_2=pos
 if(fid eq -1) then return

 ;widget input parameters
 envi_center, xoff, yoff
 base=widget_auto_base(title='Independent Analysis Confusion Matrix Input')
 sb=widget_base(base, /row, /frame)
 ofw=widget_outfm(sb, func='envi_out_check', uvalue='outf', /auto)
 ;Automanage the widget
 result=auto_wid_mng(base)
 if(result.accept eq 0) then return
 conf_doit, fid_1=fid_1, fid_2=fid_2, pos_1=pos_1, dims_1=dims_1, $
 pos_2=pos_2, dims_2=dims_2, out_name=result.outf.name, $
  in_memory=result.outf.in_memory
 endif

end
```

```
; INDEPENDENT ANALYSIS ROC MATRIX CALCULATION - J. Laurenzano - 1997

; The user must input the original image with specifically selected ROI's
; (ie not those used for classification) as the truth image.  The
; classimage is the output of the target id classification algorithm.
; The target class must be either region 1 or region 2.  The output
; matrix can be written to a file for further analysis and plotting
; using either IDL or a spreadsheet program.

pro in_roc_doit, fid_1=fid_1, fid_2=fid_2, pos_1=pos_1, pos_2=pos_2, $
dims_1=dims_1, dims_2=dims_2, out_name=out_name, $
 in_memory=in_memory, r_fid_1=r_fid_1, r_fid_2=r_fid_2, target=target

print, 'fid2', fid_2
print, 'fid1', fid_1

;Allocate memory array or open output file
get_lun, unit
if(in_memory) then mem_res=dblarr(2,2) $
 else openw, unit, out_name, /block

envi_file_query, fid_1, fname=fname, nb=nb, ns=ns, nl=nl, $
 data_type=data_type
 ns_1=ns
 nl_1=nl
print, 'ns_1', ns_1

envi_file_query, fid_2, fname=fname, nb=nb, ns=ns, nl=nl, $
 data_type=data_type
 ns_2=ns
 nl_2=nl
 print, 'ns_2', ns_2

; Retrieve classified image pixel values
data=intarr(ns_2,nl_2)

tile_id=envi_init_tile(fid_2, pos_2, num_tiles=num_tiles)
 print, 'num_tiles', num_tiles
for i=0, num_tiles-1 do begin
 data(*,i*nl_2/num_tiles:(i+1)*nl_2/num_tiles-1)=$
   envi_get_tile(tile_id, i, ys=ys, ye=ye)
 print, 'values',max(data)
 print, 'values', min(data)
endfor

; Define Target/Background Regions
```

```
if (target eq 1) then begin
 tg=0
 bg=1
endif else begin
 tg=1
 bg=0
endelse

; Define ROC matrices
roc_1=intarr(2,2)
roc_per=fltarr(2,2)

; Retrieve ROI information
roi_ids=envi_get_roi_ids(fid=fid_1)
for i=0, n_elements(roi_ids)-1 do begin
 roi_addr=envi_get_roi(roi_ids(i), roi_color=color)

 ;print, n_elements(roi_addr)
 ;print, 'rois',roi_ids

 for j=0, n_elements(roi_addr)-1 do begin
  xloc=roi_addr(j) mod ns_2
  yloc=roi_addr(j)/ns_2

  if(i eq tg) then begin
   if(data(xloc,yloc) eq tg) then begin
    roc_1(0,0)=roc_1(0,0)+1
   endif else begin
    roc_1(1,0)=roc_1(1,0)+1
   endelse
  endif else begin
   if(data(xloc,yloc) eq bg) then begin
    roc_1(1,1)=roc_1(1,1)+1
   endif  else begin
    roc_1(0,1)=roc_1(0,1)+1
   endelse
  endelse

 endfor
endfor

print, 'roc', roc_1
roc_tot=total(roc_1)
roc_per=roc_1/roc_tot * 100
print, 'percent',roc_per
```

```
if(in_memory) then mem_res=roc_per $
 else printf, unit, roc_per
free_lun, unit
cnd
;*******************************************************************
pro in_roc, ev
widget_control, ev.id, get_uvalue=uvalue
if(uvalue eq 'inroc') then begin
 envi select, title='Independent Analysis Truth Image',$
  fid=fid, dims=dims, pos=pos, /mask, /roi
 fid_1=fid
 dims_1=dims
 pos_1=pos
 if(fid eq -1) then return
 envi_select, title='Independent Analysis Classified Image', $
  fid=fid, dims=dims, pos=pos, /mask, /roi
 fid_2=fid
 dims_2=dims
 pos_2=pos
 if(fid eq -1) then return

 ;widget input parameters
 envi_center, xoff, yoff
 base=widget_auto_base(title='Independent Analysis ROC Matrix Input')

 sb=widget_base(base, /row, /frame)
 sb1=widget_base(base, /col)
 wp=widget_param(sb1, $
 prompt='Rcgion of Targct Class Rcprcscntation (1 or 2)', $
  uvalue='target', default=1, /auto)
 sb1=widget_base(base, /col)
 ofw=widget_outfm(sb1, func='envi_out_check', uvalue='outf', /auto)
 ;Automanage the Widget
 result=auto_wid_mng(base)
 if(result.accept eq 0) then return
 target=result.target
 in_roc_doit, fid_1=fid_1, fid_2=fid_2, pos_1=pos_1, dims_1=dims_1, $
 pos_2=pos_2, dims_2=dims_2, out_name=result.outf.name, $
  in_memory=result.outf.in_memory, target=target
 cndif

end
```

```
; STRATIFIED RANDOM SAMPLING CONFUSION MATRIX - J. Laurenzano 1997

; This program is designed to allow the user to input truth data
; for each randomly sampled image pixel. Initially, the program
; requires that the user enter the class map image, the original
; image, and the desired number of training pixels. The program
; later asks the user to select the three spectral bands for
; image display. The program generates random pixel coordinates
; and displays a portion of the original image with cross hairs
; marking the location of the pixel in question. The user must
; select the landcover class to which the pixel belongs. Printed
; output in the IDL window consists of a confusion matrix with
; appropriate row and column headings. The columns represent truth.
; Only the numeric portion of the confusion matrix is stored to file.
; Thus it is imperative that the user maintain thorough records for
; each file.

;***NOTE** IF -1 APPEARS IN THE PIXEL CLASS INPUT WINDOW THE USER
; SHOULD HIT OK FOR THE PIXEL SELECTION TO CONTINUE


;************************Event Handler*******************************
pro st_conf_doit_event, event

;Get the variable stored in the top level base user value
widget_control, event.top, get_uvalue=info, /no_copy

;determine which action caused the event
widget_control, event.id, get_uvalue=buttonvalue

;Proceed based on the button that was pushed
if buttonvalue EQ 'cancel' then begin
 widget_control, event.top, /destroy
 return
endif else $
 widget_control, info.tclass, get_value=str_num



;Test to see if code is working
print, 'pixel', str_num

if (str_num(0) ne -1) then begin
 if(str_num(0) eq 0) then class=info.numclass $
   else class=str_num-1
 print, 'pixel mod', class
```

```
  if(info.data(info.xloc,info.yloc) eq 0) then $
    info.confus(class,info.numclass)=info.confus(class,info.numclass)+1 $
  else $
    info.confus(class, info.data(info.xloc,info.yloc)-1)= $
     info.confus(class, info.data(info.xloc,info.yloc)-1) +1
    print, 'confus', info.confus(class, info.data(info.xloc,info.yloc)-1)
endif

;create new pixel address
s=fix((info.ns-1)*randomu(seed))+1
l=fix((info.nl-1)*randomu(seed))+1
random=l*info.ns + (s+1)
print, 'new xloc', s
print, 'new yloc', l
print, 'random', random
info.xloc=s
info.yloc=l

dims=[-1L, s-1,s-1,l-1,l-1]
pos=[0]
current=fix(envi_get_data(fid=info.fid_1, pos=pos, dims=dims))
print, 'current', current
lab_value='image pixel: ('+strtrim(s,2)+','+strtrim(l,2) +$
 '), iteration ' +strtrim(info.count)


test_1=where(info.r_matrix EQ random)
print, 'test', test_1(0)

if(test_1(0) eq -1) then begin ;test for prior selection

 if(info.num_test_pix(info.data(s,l)) $
  LT info.str_pix(info.data(s,l))) then begin

  info.r_matrix(info.count)=random

  widget_control, info.lab, set_value=lab_value


  ;clear the text widget
  widget_control, info.tclass, set_value=""

  ;increment the counter
  info.count=info.count+1
  info.r_matrix(info.count)=random
 endif else widget_control, info.tclass, set_value='-1'
```

```
 endif else widget_control, info.tclass, set_value='-1'
 print, 'numtrain', info.num_train
 print, 'count', info.count
 if(info.count GE info.num_train) then begin
  widget_control, event.top, /destroy

  print, 'Stratified random sampling confusion matrix'
  print, ' ', info.cl_names
  for i=0,info.numclass-1 do begin
   print, info.cl_names(i), info.confus(*,i)
  endfor
  print, 'noclass', info.confus(*,info.numclass)

  ; Allocate memory array or open output file
  get_lun, unit
  if(info.in_memory) then mem_res=intarr(info.numclass+1, $
   info.numclass+1) $
  else openw, unit, info.out_name

 ;store output confusion matrix
 if(info.in_memory) then mem_res=info.confus $
  else printf, unit, info.confus, info.cl_names

  free_lun, unit

  return
 endif

;return the info variable to the top level base
widget_control, event.top, set_uvalue=info, /no_copy

end


; **************************MAIN PROGRAM**********************
pro st_conf_doit, fid_1=fid_1, pos_1=pos_1, dims_1=dims_1, $
 fid_2=fid_2, dims_2=dims_2, pos_2=pos_2, out_name=out_name, $
 num_train=num_train, in_memory=in_memory, $
 r_fid_1=r_fid_1, r_fid_2=r_fid_2

; Access Class names from original image

envi_file_query, fid_2, fname=fname, nb=nb, ns=ns, nl=nl, $
 bnames=bnames, xstart=xstart, ystart=ystart
bnames_2=bnames
print, 'bnames', bnames_2
```

```
tempa=size(bnames)
name_type=tempa(2)
roi_ids=envi_get_roi_ids(fid=fid_2)
print, 'roi_ids',roi_ids
numclass=n_elements(roi_ids)
cl_names=make_array(n_elements(roi_ids), type=name_type)
for i=0, numclass-1 do begin
 roi_addr=envi_get_roi(roi_ids(i), roi_name=name)
 ;print, 'name', name
 cl_names(i)=name
endfor

print, 'class names', cl_names

; Access Class Image information
envi_file_query, fid_1, fname=fname, nb=nb, ns=ns, nl=nl, $
 bnames=bnames, xstart=xstart, ystart=ystart
;dn=0
;envi_disp_query, dn,xds=xds, yds=yds, fid=fid_1, $
;  color=color



;**************Count pixels in each class************************
; Read in file data
; Initialize data tile
tile_id=envi_init_tile(fid_1, pos_1, num_tiles=num_tiles, interleave=0)
print, 'num_tiles', num_tiles
; Count class pixels\
data = intarr(ns,nl)
for i=0, num_tiles-1 do begin
 data(*,i*nl/num_tiles:(i+1)*nl/num_tiles-1)= $
    envi_get_tile(tile_id, i, ys=ys, ye=ye)
endfor

print, 'max', max(data)
numclass=max(data)
tot=ns*nl
;print, 'total', tot
numpix=lonarr(numclass+1)
for i=0, ns-1 do begin
 for j=0, nl-1 do begin
 numpix(data(i,j))=numpix(data(i,j))+1
 endfor
endfor
```

```
;print, 'numpix', numpix
print, 'total', total(numpix)
;Calculate stratified number of pixels
str_pix=lonarr(numclass+1)
str_pix=fix(num_train*numpix/tot)
print, 'str_pix', str_pix

;*************Generate random coordinate set*************************

r_matrix=lonarr(tot) ;records randomly selected coordinate values
num_test_pix=lonarr(numclass+1) ;records number of pixels per class
confus=intarr(numclass+1,numclass+1)

; Generate initial random coordinate set

xloc=fix((ns-1)*randomu(seed))+1
print, 'ns', ns
print, 'nl', nl
yloc=fix((nl-1)*randomu(seed))+1
random=yloc*ns + (xloc+1)
r_matrix(0)=random
count=0

; get the pixel's currently defined class value

dims=[-1L, xloc-1, xloc-1, yloc-1, yloc-1]
pos=[0]
current=fix(envi_get_data(fid=fid_1, pos=pos, dims=dims))
print, 'current', current

; Create the user interface
envi_center,xoff,yoff
tlb=widget_base(/col,/frame, xoff=xoff, yoff=yoff)
sbase1=widget_base(tlb, /row)
lab_value='image pixel: ('+strtrim (xloc,2)+','+strtrim(yloc,2)+$
 '), iteration 1'; '+strtrim(current(0),2)
lab1=widget_label(sbase1, value=lab_value, /align_center)
sbase2=widget_base(tlb, title='Available Class Regions',/frame, /row)
label2=widget_list(sbase2, value=cl_names)
sbase3=widget_base(tlb, /frame, /row)
label3=widget_label(sbase3, value="Enter the pixel's true class:")
tclass=widget_text(sbase3, /editable, uvalue='tclass')
sbase4=widget_base(tlb, /frame, /row)
c_button=widget_button(sbase4, value='Cancel', uvalue='cancel')
ok_button=widget_button(sbase4, value='OK', uvalue='ok')
```

```
; Save information that must be passed between the main procedure and
; the event handler

info={tclass:tclass, fid_1:fid_1,ns:ns,nl:nl,str_pix:str_pix, $
  count:count, cl_names:cl_names, in_memory:in_memory, $
 r_matrix:r_matrix, num_test_pix:num_test_pix, confus:confus, $
  data:data,xloc:xloc,yloc:yloc,current:current, lab_value:lab_value,$
 numclass:numclass, num_train:num_train,fid_2:fid_2,out_name:out_name}

widget_control, tlb, set_uvalue=info, /no_copy

;Realize the GUI and start the Xmanager loop
widget_control, tlb, /realize
xmanager, 'st_conf_doit', tlb, event_handler='st_conf_doit_event'
end
;*********************************************************************
pro st_conf, ev

widget_control, ev.id, get_uvalue=uvalue
if(uvalue eq 'stratified') then begin
 ;Get input file

 envi_select, title='Stratified Random Sampling Class Map',$
  fid=fid, dims=dims, pos=pos, /mask, /roi
  fid_1=fid
  dims_1=dims
  pos_1=pos
  if(fid eq -1) then return

 envi_select, title='Stratified Random Sampling Original Image',$
  fid=fid, dims=dims, pos=pos, /mask, /roi
  fid_2=fid
  dims_2=dims
  pos_2=pos
  if(fid eq -1) then return
 if(fid eq -1) then return

 ;Widget input parameters
 envi_center, xoff,yoff
 base=widget_auto_base(title='Stratified Random Sampling Input Parameters')
 sb=widget_base(base, /column, /frame)
 sb1=widget_base(sb, /row)
 wp=widget_param(sb1, prompt='Number of Training Points', dt=2, $
  xs=6, uvalue='num_train', /auto)
 sb1=widget_base(sb, /row)
 ofw=widget_outfm(sb, func='envi_out_check', uvalue='outf', /auto)
```

```
 ; Automanage the widget
 result=auto_wid_mng(base)
 if(result.accept eq 0) then return
 num_train=result.num_train
 st_conf_doit, fid_1=fid_1, pos_1=pos_1, dims_1=dims_1, $
  fid_2=fid_2, pos_2=pos_2, dims_2=dims_2,out_name=result.outf.name, $
  in_memory=result.outf.in_memory, num_train=num_train
endif
end
```

```
; STRATIFIED RANDOM SAMPLING CONFUSION MATRIX - J. Laurenzano 1997

; This program is designed to allow the user to input truth data
; for each randomly sampled image pixel. Initially, the program
; requires that the user enter the class map image, the original
; image, and the desired number of training pixels. The program
; later asks the user to select the three spectral bands for
; image display. The program generates random pixel coordinates
; and displays a portion of the original image with cross hairs
; marking the location of the pixel in question. The user must
; select the landcover class to which the pixel belongs. Printed
; output in the IDL window consists of a confusion matrix with
; appropriate row and column headings. The columns represent truth.
; Only the numeric portion of the confusion matrix is stored to file.
; Thus it is imperative that the user maintain thorough records for
; each file.

;***NOTE** IF -1 APPEARS IN THE PIXEL CLASS INPUT WINDOW THE USER
; SHOULD HIT OK FOR THE PIXEL SELECTION TO CONTINUE


;****************Event Handler**********************************
pro st_roc_doit_event, event

;Get the variable stored in the top level base user value
widget_control, event.top, get_uvalue=info, /no_copy

;determine which action caused the event
widget_control, event.id, get_uvalue=buttonvalue

;Proceed based on the button that was pushed
if buttonvalue EQ 'cancel' then begin
 widget_control, event.top, /destroy
 return
endif else $
 widget_control, info.tclass, get_value=str_num



 ;Test to see if code is working
print, 'pixel', str_num

if (str_num(0) ne -1) then begin
  if(str_num(0) eq 0) then class=info.numclass $
  else class=str_num
  print, 'pixel mod', class
```

```
    print, 'target', info.target
    print, 'data', info.data(info.xloc,info.yloc)
    ;stop
    if(info.data(info.xloc,info.yloc) eq info.target-1) then begin
      if(class(0)-1 eq info.data(info.xloc,info.yloc)) then $
        info.roc_mat(0,0)=info.roc_mat(0,0)+1 $
      else info.roc_mat(0,1)=info.roc_mat(0,1)+1
    endif else begin
      if(class(0)-1 eq info.data(info.xloc,info.yloc)) then $
        info.roc_mat(1,1)=info.roc_mat(1,1)+1 $
      else info.roc_mat(1,0)=info.roc_mat(1,0)+1
    endelse
  endif


;create new pixel address
s=fix((info.ns-1)*randomu(seed))+1
l=fix((info.nl-1)*randomu(seed))+1
random=l*info.ns + (s+1)
print, 'new xloc', s
print, 'new yloc', l
print, 'random', random
info.xloc=s
info.yloc=l

dims=[-1L, s-1,s-1,l-1,l-1]
pos=[0]
current=fix(envi_get_data(fid=info.fid_1, pos=pos, dims=dims))
print, 'current', current+1
lab_value='image pixel: ('+strtrim(s,2)+','+strtrim(l,2) +$
  ')';, currently assigned to class '+strtrim(current(0),2)


test_1=where(info.r_matrix EQ random)
print, 'test', test_1(0)

if(test_1(0) eq -1) then begin ;test for prior selection

 if(info.num_test_pix(info.data(s,l)) $
   LT info.str_pix(info.data(s,l))) then begin

   info.r_matrix(info.count)=random

   widget_control, info.lab, set_value=lab_value
```

```
    ;clear the text widget
    widget_control, info.tclass, set_value=""

    ;increment the counters
    info.count=info.count+1
    info.r_matrix(info.count)=random
    info.num_test_pix(info.data(s,l))=info.num_test_pix(info.data(s,l))+1
  endif else widget_control, info.tclass, set_value='-1'
 endif  else widget_control, info.tclass, set_value='-1'
 print, 'numtrain', info.num_train
 print, 'count', info.count
 if(info.count GE info.num  train) then begin
  widget_control, event.top, /destroy

  roc_per=fltarr(2,2) ; Percentage matrix
  roc_tot=total(info.roc_mat)
  roc_per=info.roc_mat/roc_tot*100
  print, 'Stratificd Random Sampling ROC Matrix'
  print,  'Hit', 'Miss'
  print,  info.roc_mat
  print, 'False', 'Correct'
  print, 'Alarm', 'Rejection'
  print, 'Stratified Random Sampling Percentage Matrix'
  print,  'Hit', 'Miss'
  print,  roc_per
  print, 'False', 'Correct'
  print, 'Alarm', 'Rejection'

  ; Allocate memory array or open output file
  get_lun, unit
  if(info.in_memory) then mem_res=intarr(2,2) $
  clsc opcnw, unit, info.out_namc

  ; Store output roc matrix
  if(info.in_memory) then mem_res=roc_per $
  else writeu, unit, info.roc_mat,'percentage', roc_per
  free_lun, unit


  return
 endif

;return the info variable to the top level base
widget_control, event.top, set_uvalue=info, /no_copy

end
```

```
; ***************************MAIN PROGRAM**********************
pro roc_doit, fid_1=fid_1, pos_1=pos_1, dims_1=dims_1, $
 fid_2=fid_2, pos_2=pos_2, dims_2=dims_2, out_name=out_name, $
 num_train=num_train, in_memory=in_memory,target=target, $
 r_fid_1=r_fid_1, r_fid_2=r_fid_2


; Access Class names from original image

envi_file_query, fid_2, fname=fname, nb=nb, ns=ns, nl=nl, $
  bnames=bnames, xstart=xstart, ystart=ystart
bnames_2=bnames
print, 'bnames', bnames_2
tempa=size(bnames)
name_type=tempa(2)
roi_ids=envi_get_roi_ids(fid=fid_2)
print, 'roi_ids',roi_ids
numclass=n_elements(roi_ids)
cl_names=make_array(n_elements(roi_ids), type=name_type)
for i=0, numclass-1 do begin
 roi_addr=envi_get_roi(roi_ids(i), roi_name=name)
 print, 'name', name
 cl_names(i)=name
endfor

print, 'class names', cl_names

; Access Class Image information
envi_file_query, fid_1, fname=fname, nb=nb, ns=ns, nl=nl, $
 bnames=bnames, xstart=xstart, ystart=ystart


;**************Count pixels in each class************************
; Read in file data
; Initialize data tile
tile_id=envi_init_tile(fid_1, pos_1, num_tiles=num_tiles, interleave=0)
print, 'num_tiles', num_tiles
; Count class pixels
data=intarr(ns,nl)
for i=0, num_tiles-1 do begin
 data(*,i*nl/num_tiles:(i+1)*nl/num_tiles-1)= $
    envi_get_tile(tile_id, i, ys=ys, ye=ye)
endfor
```

```
print, 'max', max(data)
numclass=max(data)
tot=ns*nl
;print, 'total', tot
numpix=lonarr(numclass+1)
for i=0, ns-1 do begin
 for j=0, nl-1 do begin
 numpix(data(i,j))=numpix(data(i,j))+1
 endfor
endfor
print, 'numpix', numpix
print, 'total', total(numpix)
;Calculate stratified number of pixels
str_pix=lonarr(numclass+1)
str_pix=num_train*numpix/tot

;*************Generate random coordinate set*************************

r_matrix=lonarr(tot)          ; records randomly selected coordinate values
num_test_pix=lonarr(numclass+1)  ; records number of pixels per class
roc_mat=intarr(2,2) ; ROC matrix


; Generate intial random coordinate set
xloc=fix((ns-1)*randomu(seed))
print, 'ns', ns
print, 'nl', nl
yloc=fix((nl-1)*randomu(seed))
random=yloc*ns + (xloc+1)
count=0

; get the pixel's currently defined class value

dims=[-1L, xloc-1, xloc-1, yloc-1, yloc-1]
pos=[0]
current=fix(envi_get_data(fid=fid_1, pos=pos, dims=dims))
print, 'current', current+1


; Create the user interface
envi_center,xoff,yoff
tlb=widget_base(/col,/frame, xoff=xoff, yoff=yoff)
sbase1=widget_base(tlb, /row)
lab_value='image pixel: ('+strtrim (xloc,2)+','+strtrim(yloc,2)+$
 ')';, currently assigned to class '+strtrim(current(0),2)
lab1=widget_label(sbase1, value=lab_value, /align_center)
```

```
sbase2=widget_base(tlb, title='Available Class Regions',/frame, /row)
label2=widget_list(sbase2, value=cl_names)
sbase3=widget_base(tlb, /frame, /row)
label3=widget_label(sbase3, value="Enter the pixel's true class:")
tclass=widget_text(sbase3, /editable, uvalue='tclass')
sbase4=widget_base(tlb, /frame, /row)
c_button=widget_button(sbase4, value='Cancel', uvalue='cancel')
ok_button=widget_button(sbase4, value='OK', uvalue='ok')

; Save information that must be passed between the main procedure and
; the event handler

info={tclass:tclass, fid_1:fid_1,ns:ns,nl:nl,str_pix:str_pix, $
  count:count, cl_names:cl_names, in_memory:in_memory, $
 r_matrix:r_matrix, num_test_pix:num_test_pix, roc_mat:roc_mat, $
  data:data,xloc:xloc,yloc:yloc,current:current,lab:lab1, $
 numclass:numclass, num_train:num_train,fid_2:fid_2,out_name:out_name, $
 target:target}

widget_control, tlb, set_uvalue=info, /no_copy

;Realize the GUI and start the Xmanager loop
widget_control, tlb, /realize
xmanager, 'roc_doit', tlb, event_handler='st_roc_doit_event'

end

;*************************************************************************
pro st_roc, ev

widget_control, ev.id, get_uvalue=uvalue
if(uvalue eq 'stratroc') then begin
 ;Get input file
 envi_select, title='Stratified Random Sampling Class Map',$
  fid=fid, dims=dims, pos=pos, /mask, /roi
 fid_1=fid
 dims_1=dims
 pos_1=pos
 if(fid eq -1) then return

 envi_select, title='Stratified Random Sampling Original Image',$
  fid=fid, dims=dims, pos=pos, /mask, /roi
 fid_2=fid
 dims_2=dims
 pos_2=pos
 if(fid eq -1) then return
```

```
;Widget input parameters
envi_center, xoff,yoff
base=widget_auto_base(title='Stratified Random Sampling Input Parameters')
sb=widgct_basc(basc, /column, /framc)
sb1=widget_base(sb, /row)
wp=widget_param(sb1, prompt='Number of Training Points', dt=2, $
 xs=6, uvalue='num_train', /auto)
sb1=widget_base(base, /col)
wp=widget_param(sb1, $
 prompt='Region of Target Class Representation (1 or 2)', $
 uvalue='target', default=1, /auto)
sb1=widget_base(sb, /row)
ofw=widget_outfm(sb, func='envi_out_check', uvalue='outf', /auto)
; Automanage the widget
result=auto_wid_mng(base)
if(result.accept eq 0) then return
num_train=result.num_train
target=result.target
roc_doit, fid_1=fid_1, pos_1=pos_1, dims_1=dims_1, $
 fid_2=fid_2, pos_2=pos_2, dims_2=dims_2, out_name=result.outf.name, $
  in_memory=result.outf.in_memory, num_train=num_train, target=target
endif

end
```