ASSESSING RESOLUTION TRADEOFFS OF REMOTE SENSING DATA VIA
CLASSIFICATION ACCURACY CUBES FOR SENSOR
SELECTION AND DESIGN

By
Wesley Johnson

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By

Wesley Johnson

Approved:

Dr. Lori Mann Bruce
Associated Professor of Electrical and
Computer Engineering
(Director of Thesis)

Dr. Roger L. King
Giles Distinguished Professor of
Electrical and Computer Engineering
(Committee Member)

Dr. Nicholas H. Younan
Professor of Electrical and
Computer Engineering
(Committee Member and Graduate
Coordinator)

Dr. Kirk H. Schulz
Dean of the Bagley College of
Engineering
Name: Wesley Johnson

Date of Degree: May 13, 2006

Institution: Mississippi State University

Major Field: Electrical Engineering

Major Professor: Dr. Lori Mann Bruce

Title of Study: ASSESSING RESOLUTION TRADEOFFS OF REMOTE SENSING DATA VIA CLASSIFICATION ACCURACY CUBES FOR SENSOR SELECTION AND DESIGN

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Candidate for Degree of Master of Science

An investigation has been done on classification accuracy data cubes for use in the determination of spectral, spatial, and temporal sensor resolution requirements. The data cube is the result of an automatic target recognition (ATR) system that creates and combines reduced spectral and spatial resolution datasets. Datasets are subjected to the Best Spectral Bands (BSB) and the All Spectral Bands (ASB) testing method approaches and nearest mean (NM) and maximum likelihood (ML) classifiers. The effectiveness of the system is tested via two target-nontarget case studies, namely, terrestrial Cogongrass (Imperata cylindrica)-Johnsongrass (Sorghum halepense) and aquatic Water Hyacinth (Eichhornia crassipes)-American Lotus (Nelumbo lutea). Results reveal the effects of spectral-spatial-temporal resolution combinations on the ability of an ATR system to accurately detect the target invasive species. The ATR system demonstrates the use of resolution cubes that can be readily used to design or select cost-effective sensors for use in invasive species target detection.
DEDICATION

This thesis is dedicated to my family, who have always pushed me to do my best in everything and have taught me that any goal is within reach if I am willing to give it my all. I also dedicate this thesis to every faculty member, teacher, and professor that I have ever had at any school. Your belief in me has helped me to believe in myself. May God's gentle graces be with you always.
ACKNOWLEDGEMENTS

I would like to thank Dr. Lori Mann Bruce for being such a wonderful academic and personal advisor throughout my career here at Mississippi State University. I thank her and for her invaluable guidance while I did research and wrote my thesis. I would to thank Dr. Nicholas H. Younan and Dr. Roger L. King for serving on my committee. I would also like to thank my friends and family for their support throughout this time.
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<td>Classification accuracies for the ASB approach for the sensor profiles of the Water Hyacinth-American Lotus dataset.................................</td>
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CHAPTER I
INTRODUCTION

Invasive species can be defined as organisms that, primarily introduced by humans, are non-native to a region and whose introduction has or may have adverse effects on the ecosystem of that region. A highly problematic terrestrial invasive species in the southeastern United States is Cogongrass (*Imperata cylindrica*), a weed that is known to facilitate wildfires and overtake native vegetation, such as the structurally similar Johnsongrass (*Sorghum halepense*), effectively causing high damage to other organisms’ habitats [1]. Water Hyacinth (*Eichhornia crassipes*) and American Lotus (*Nelumbo lutea*) are two highly problematic aquatic invasive species. These rapidly-producing plants are known to overtake lakes and ponds seemingly overnight, and the amount spent on the management of each species is in the millions of dollars [2-3]. As with Cogongrass, Water Hyacinth and American Lotus are very difficult pests to control. An increasingly important issue has been to monitor the growth and migration of these invasive species using remotely sensed data. Pictures comparing Cogongrass to Johnsongrass and Water Hyacinth to American Lotus are shown in Figures 1.1 and 1.2, respectively. [1-5].
Many federal agencies and commercial companies undertake projects that involve the detection of a remotely sensed target, such as Cogongrass. There is a need for a process by which agencies/companies can easily determine what resolution combinations are acceptable for the levels of accuracy that are necessary for their project(s). For this purpose, this thesis propose(s) the solution of a 3D resolution cube, from which 2D resolution maps based on the selection of one resolution can be generated. The maps can be used to determine optimum combinations of resolution for a given application. The
optimality is based on maximizing target detection accuracies. The optimum resolution specifications can then be used to appropriately select an existing sensor or design a new sensor for the given application. In this thesis, the design and use of resolution cubes is demonstrated via an invasive species application, namely, detecting the target Cogongrass from Johnsongrass and the target Water Hyacinth from American Lotus.

This thesis provides the reader with a detailed discussion of the resolution data cube system. Chapter 2 provides a review discussing the current state of knowledge as it applies to remote sensing. Chapter 3 discusses in detail the methodologies employed in developing the proposed system. Chapter 4 provides results in the form of 3D resolution cubes and 2D resolution maps. Chapter 5 discusses the results and draws appropriate and relevant conclusions about the proposed system. Chapter 6 provides details on the implications given by the system and discussion about possible future work.
CHAPTER II
BACKGROUND AND CURRENT STATE OF KNOWLEDGE

2.1 Data Resolution

Data resolution is very important to a remote sensing system’s ability to distinguish between classes. The four major types of resolutions that can be enhanced or degraded are spectral resolution, spatial resolution, temporal resolution, and radiometric resolution. Spectral resolution deals with the actual number or wavelengths or spectral bands available in a signal. Spatial resolution can be thought of as the number of pixels per unit area in an image – the more pixels that are in an area of an image, the more detail that can be seen in that area. Temporal resolution applies to data that has been collected at more than one time for the same target(s). The higher the temporal resolution, the more times the data from the same target(s) has been collected over a given period of time. Radiometric resolution is determined by the number of bits per pixel in an image.

2.1.1 Spectral Resolution

Spectral resolution “refers to the number and dimension of specific wavelength intervals in the electromagnetic spectrum to which a sensor is sensitive” [6]. For a hyperspectral signature, this corresponds to the number of spectral bands that are available for analysis. Typically, it is assumed that an increase in the number of spectral bands will result in an increase in target detection accuracies. Spectral resolution can be
viewed in many ways, such as the number of bands in a signal, the spectral sampling period (separation between adjacent band center points), the FWHM, or 2 times the FWHM (if accounting for Nyquist Theory). In this thesis, the spectral resolution is defined as the FWHM. That is, the sampling period and the FWHM are equivalent.

There are various multispectral and hyperspectral sensors in use today. Examples of these types of sensors include the multispectral Landsat-7 and Advanced Land Imager (ALI) sensors and the hyperspectral Hyperion sensor. All three sensors were produced by NASA for the purpose of observing and characterizing the earth’s surface and are a part of the Global Earth Observation System of Systems (GEOSS). The Hyperion sensor resolves 220 spectral bands in the range of 0.4 – 2.5µm with a spatial resolution of 30m for each band [7]. This results in very high spectral resolution image data for use in remote sensing applications. The multispectral sensors give much lower spectral resolution data, with only around seven to nine spectral bands being resolved in the 0.4 – 2.5 µm range. Tables 2.1 and 2.2 give the spectral/spatial information regarding the Landsat-7 and ALI sensors, respectively [8-9].

Table 2.1  Landsat-7 Spectral/Spatial Characteristics

<table>
<thead>
<tr>
<th>Band Number</th>
<th>Spectral Range (µm)</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.45 – 0.515</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>0.525 – 0.605</td>
<td>30</td>
</tr>
<tr>
<td>3</td>
<td>0.63 – 0.690</td>
<td>30</td>
</tr>
<tr>
<td>4</td>
<td>0.75 – 0.90</td>
<td>30</td>
</tr>
<tr>
<td>5</td>
<td>1.55 – 1.75</td>
<td>30</td>
</tr>
<tr>
<td>6</td>
<td>10.40 – 12.5</td>
<td>60</td>
</tr>
<tr>
<td>(thermal infrared channel)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>2.09 – 2.35</td>
<td>30</td>
</tr>
<tr>
<td>Pan</td>
<td>0.52 – 0.90</td>
<td>15</td>
</tr>
</tbody>
</table>
Table 2.2  ALI Spectral/Spatial Characteristics

<table>
<thead>
<tr>
<th>Band Number</th>
<th>Spectral Range (µm)</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.433 – 0.453</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>0.45 – 0.515</td>
<td>30</td>
</tr>
<tr>
<td>3</td>
<td>0.525 – 0.605</td>
<td>30</td>
</tr>
<tr>
<td>4</td>
<td>0.63 – 0.69</td>
<td>30</td>
</tr>
<tr>
<td>5</td>
<td>0.775 – 0.805</td>
<td>30</td>
</tr>
<tr>
<td>6</td>
<td>0.845 – 0.89</td>
<td>30</td>
</tr>
<tr>
<td>7</td>
<td>1.2 – 1.3</td>
<td>30</td>
</tr>
<tr>
<td>8</td>
<td>1.55 – 1.75</td>
<td>30</td>
</tr>
<tr>
<td>9</td>
<td>2.08 – 2.35</td>
<td>30</td>
</tr>
<tr>
<td>Panchromatic</td>
<td>0.48 – 0.69</td>
<td>10</td>
</tr>
</tbody>
</table>

Various aspects of spectral resolution have been involved in many different applications over the years. Kauppinen and Roth used spectral resolution enhancement to improve noise reduction in audio signals [10]. In remote sensing, Graham et al. used low spectral resolution Landsat-7 data to explore the interactions between rodents and vegetation as linked to disease transmission [11]. In an earlier study, Danson et al. used data with high spectral resolution to determine leaf water content. The data was obtained via a spectroradiometer that measured from 400nm to 2500nm [12]. Herold et al. studied the effects of different spectral resolutions on spatial data used in mapping of urban areas [13]. In related research, Kerekes et al. developed methods for quantitatively forecasting remote sensing system functionality depending on given degradation conditions, such as atmospheric noise, particularly for spectral imaging systems [14-15].

There is a general assumption that higher spectral resolution is always better; however, this assumption is not always true. Sometimes it may be necessary, even desirable, to use filters to “smooth” the given data. An example of this type of situation
would be one in which lowpass or Savitzky-Golay filters are used to remove noise from data [16-17].

2.1.2 Spatial Resolution

“Spatial resolution is a measure of the smallest angular or linear separation between two objects that can be resolved” in a remotely sensed image [6]. For example, one would typically need a spatial resolution of about 1 meter to clearly see a sidewalk, but a lower spatial resolution would suffice to distinguish between houses and roads.

As with spectral resolution, there are many sensors used in applications today that employ varying spatial resolutions. Some of these sensors include the Landsat-7, Systeme Probatoire l’Observation de la Terre (SPOT)-5, and QuickBird sensors. These sensors were all produced with the purpose of monitoring and accurately characterizing the earth’s surface. The Landsat-7 sensor has, as seen in Table 2.1, relatively low spatial resolution by today’s standards, but it can be used to study large areas [8]. Spatial resolutions for the SPOT-5 sensor, shown in Table 2.3, are much higher than those for the Landsat-7 sensor and can be used to study much smaller areas [18]. QuickBird, one of the best spatial sensors available today, boasts spatial resolutions high enough to classify street signs on a highway. These resolutions can be seen in Table 2.4 [19].

Table 2.3  SPOT-5 Spatial Characteristics

<table>
<thead>
<tr>
<th>Band Type</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panchromatic</td>
<td>2.5 – 5</td>
</tr>
<tr>
<td>Multispectral</td>
<td>10</td>
</tr>
<tr>
<td>Short Wave Infrared</td>
<td>20</td>
</tr>
</tbody>
</table>
Table 2.4  QuickBird Spatial Characteristics

<table>
<thead>
<tr>
<th>Band Type</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panchromatic</td>
<td>0.61 – 0.72</td>
</tr>
<tr>
<td>Multispectral</td>
<td>2.44 – 2.88</td>
</tr>
</tbody>
</table>

Mercier et al. developed a technique that used higher resolution High Resolution Visible and Infrared (HRVIR) spatial data to assess changes observed in winter vegetation data that was collected using the lower resolution SPOT VEGETATION sensor [20]. Using even lower resolution Landsat data, Duffett et al. characterized areas of Australia’s Northern Territory for saltwater crocodile nesting habitats [21]. Boccardo et al. used pan-sharpened Landsat and QuickBird imagery to classify urban environments [22]. In the medical field, Xiaochuan et al. used the combination of a fan-beam configuration and an algorithm for data reconstruction to enhance the spatial resolution in computed tomography, or X-rays [23].

Similar to the idea given by spectral resolution, it is generally assumed that an increase in spatial resolution results in higher target detection accuracies. However, this is not always the case. For example, one would typically not want a sensor with a spatial resolution of only 5 meters if the desired application was to monitor large-scale wildfires in the southwestern desert of the United States.

2.1.3 Temporal Resolution

Temporal resolution refers to how often data in a certain scene is recorded [6]. For example, if a satellite that has a temporal resolution of four days, it means that the
satellite images the same scene every 4 days. Table 2.5 shows several satellite sensors and their respective temporal resolutions [8, 18-19].

Table 2.5 Satellite Sensor Temporal Resolutions

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Temporal Resolution (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>QuickBird</td>
<td>1 – 3.5</td>
</tr>
<tr>
<td>SPOT-5</td>
<td>2 – 3</td>
</tr>
<tr>
<td>Landsat-7</td>
<td>16</td>
</tr>
</tbody>
</table>

As with spectral and spatial resolutions, temporal resolution can play a key part in remote sensing applications. McKellip *et al.* proposed a surveillance system that used multitemporal Moderate Resolution Imaging Spectrometer (MODIS) data to produce near-daily Normalized Difference Vegetation Index (NDVI) products for the purpose of quick and effective response to disease outbreaks among crops [24]. Mathur *et al.* used hyperspectral-multitemporal data features along with a greedy search algorithm to distinguish between aquatic weed species and also developed a wavelet-based feature extraction method for use with temporal vegetation signatures generated using MODIS imagery [25-26]. Also, Dell’Acqua *et al.* used multitemporal synthetic aperture radar (SAR) images to improve urban area characterization [27].

Once again, it is typically assumed that higher resolution, in this case temporal resolution, is always better for the applications in which it is involved. Nevertheless, it could be argued that this assumption is not necessarily true. For example, consider a project in which one was to study the effects of the earth’s seasons on a specific target. It might be more appropriate to collect data weekly or monthly rather than every day, since
the effects of the seasons, and not the effects of the specific details and occurrences within the seasons, would be studied.

2.2 Data Reduction

2.2.1 Averaging

The amount of data recorded by a system can be reduced by averaging certain portions of the data. This is akin to lowpass filtering, or smoothing, of the data. Backer et al. used this idea of averaging in their study of hyperspectral data classification. After selecting the best features of the given data, the selected features were averaged spectrally with their respective local features in order to optimally reduce data dimensionality, thereby achieving the best possible classification accuracies [28]. A similar technique was used by Venkataraman, as windows of spectral bands were averaged to create an optimal dataset for classification [29]. These techniques are similar to the Savistky-Golay method, which smooths datasets by fitting polynomial functions of varying degrees to those datasets [30]. In radar, Monakov et al. used spatial averaging to design a practical polarimetric scatterometer system [31].

2.2.2 Wavelets

Wavelets are really a collection of ideas rather than a single technique. Their roots can be found in mathematics, civil engineering, electrical engineering, computer science, and physics. They get their name from the fact that they are “small waves.” In the same way that Fourier analysis can be used to reconstruct signals from many sine waves, wavelet analysis can be used to reconstruct signals from many “prototype” waves,
where the “prototype” is a wavelet function. For example, the wavelet function could be a windowed square wave or a windowed sine wave. Wavelets are a powerful signal processing tool because they allow for multiresolution analysis [32].

In the area of remote sensing, wavelets have been used to analyze hyperspectral reflectance, extract features, and provide feature dimensionality reduction using subsets or combinations of wavelet coefficients. Wavelets have also been used for texture analysis in the spatial domain [33-36].

2.2.3 Principal Component Analysis

Component analysis is concerned with finding the direction(s) in a feature space that give(s) lower-dimensional representations for given data. Using principal component analysis (PCA), these directions are the eigenvectors corresponding to the largest eigenvalues of the covariance matrix for a given data set. The resulting coefficients, or principal components, are useful for representing data, and have been widely used for data compression and feature extraction in remotely sensed data [37-40].

While PCA is a useful method for representing data, and an optimal one for data compression in the sense of improved mean square error (MSE), it may or may not be the best choice when attempting to extract features for the purpose of discriminating between classes [37]. Malhi et al. developed a successful PCA-driven feature selection scheme for use in the supervised and unsupervised classifications of possibly defective machine bearings [41]. Stamkopoulos et al. used a nonlinear PCA method to extract features from patient electrocardiograms for improved classification accuracies of ischemic cardiac beats [42]. Alternately, Cheriyadat and Bruce found that PCA was not necessarily an
appropriate method for feature extraction when using hyperspectral data for target
detection, since PCA is an unsupervised approach that is based on the covariance matrix
of the entire given dataset [43].

2.2.4 Linear Discriminant Analysis

Fisher's linear discriminant analysis (LDA) is a method that has been widely
employed in the area of feature extraction and optimization [44-47]. LDA determines the
best direction along which data can be projected in terms of class separation. It gives a
linear function that maximizes the ratio of interclass variance to intraclass variance. In
other words, it helps to separate given classes from each other and to compact the data
samples of each individual class into tighter clusters. The overall result is a greatly
reduced feature space dimensionality with the best possible class separations that will aid
in class discrimination [37]. However, just because LDA is specifically aimed at
reducing feature dimensionality for use in discrimination does not mean that is the best
method for every situation. For example, if the probability density function of one class
is contained within the probability density function of another class, no amount of linear
discriminant analysis will result in adequate classification accuracies [37]. In these
situations, a non-linear discriminant analysis method is required.

2.2.5 Optimal Data Grouping

When dealing with large data sets, it is sometimes a good approach to group the
data. This grouping provides for data reduction, and, when it is done optimally, it can
achieve high classification accuracies. One such optimal data grouping method is the spectral band grouping method, or, the best bands method [28].

The idea behind best bands is to find the best possible combination of features, in this case bands, that gives the maximum area, $A_z$, underneath the receiver operating characteristic (ROC) curve. The best band combinations are found by an iterative operation. The first two bands are combined, and ROC analysis is performed. This is repeated until all possible combinations of two bands are analyzed, and the combination with the best $A_z$ value is kept. Next, a third band is combined, and ROC analysis is performed in order to determine that band’s contribution. If the added band gives a better $A_z$ value, then it is kept. Otherwise it is discarded from the group. This process of keeping or discarding bands leads to the best band combination that gives the best, or highest, $A_z$ value. This means that the resulting combination of features, or bands, is the best for use in discrimination between two classes [28-29].

The best bands method has been applied in several applications. For example, Serpico et al. used the best bands method to optimally group hyperspectral signature bands to aid in optimizing the classification accuracies associated with specific image data, such as Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data [48]. Mathur also used the best bands method for using hyperspectral signatures to detect Cogongrass from other grasses [49]. Similarly, Chang et al. developed a band selection technique based on a combination of the best bands method with a band decorrelation method for use in hyperspectral image classification [40].
2.3 Data Classification

2.3.1 Nearest Neighbor

The nearest neighbor (NN) approach is used to classify samples according to the manner implied by its name. An unknown sample is placed in a feature space with multiple training samples. The Euclidean distance between the unknown sample and each training sample is calculated, and the sample is classified according to a function of the distances obtained, as defined by the creator of the classifier. One common function is to classify the test sample as the same class as its nearest neighbor. Other functions are based on $K$ nearest neighbors (KNN), where $K$ can range from one to $N$, with $N$ being the total number of training samples. When using $K$ nearest neighbors, the classification can be based on a simple majority rule, or the function can be a weighted average where the weights are based on the distance of the neighbor from the test sample. For example, the weights can be the reciprocal of the neighbor’s Euclidean distance from the test sample [37].

Various remote sensing applications have used nearest-neighbor classifiers. Yu et al. used a fuzzy KNN classifier to classify genetic features extracted from AVIRIS imagery [50]. Mathur et al. used a NN classifier to discriminate between subtly different vegetative hyperspectral signatures [51]. Hardin et al. used six different NN classifiers to study Landsat image data [52].
2.3.2 Nearest Mean

A nearest mean (NM) classifier discriminates between test samples based on their distance from the class means of the training samples in a given feature space. An unknown sample is introduced into a feature space. Training data consisting of several classes may exist in this feature space. The mean of each existing training class is calculated, and the Euclidean distance between the test sample and each mean is determined, with the closest mean being the class to which the test sample is classified [37].

Like the nearest neighbor classifiers, nearest mean classifiers have also been widely used in remote sensing applications. Jiang et al. used a NM classifier to classify hyperspectral kudzu signatures that had been subjected to Haar wavelet analysis [53]. Smits used a NM classifier as part of a multiclassifier system for use with supervised remote sensing image classification [54]. Zhang et al. used a NM classifier for classifying hyperspectral soil textures [55].

2.3.3 Maximum Likelihood

Maximum likelihood (ML) techniques use the assumption that a given sample value is fixed but unknown. The best estimate, or the value that is the most likely, is the one that maximizes the probability of obtaining the samples already observed. The ML classification method has several nice attributes, such as good convergence with an increasing number of training samples and relatively simple implementation when compared with other methods [37].
Classifiers that use the ML technique can be found in numerous systems for use in target and pattern recognition with regard to remote sensing. For example, Challenor et al. used a ML model to estimate several geophysical parameters involved in radar altimetry, including the significant wave height and the skewness of the sea [56]. Byeungwoo and Landgrebe also used a ML classifier in their partially supervised classification approach for weighted clustering [57].

2.3.4 Testing Methods

The methods used to test the data also have an impact on a system’s ability to distinguish between classes of data. \( N \)-fold cross validation is a common way to check, or validate the accuracies achieved by a given system [58]. Varying \( N \) results in different testing methods for the system. When \( N \) equals one, the data is biased, as the training and testing data are identical. When \( N \) equals two, jackknifing is employed. Jackknifing (JK) is a common data separation technique in which half of a data set consisting of randomly shuffled samples is extracted as training data. The classification system is then tested on the remaining data samples. This approach removes bias, as the training and testing datasets are mutually exclusive. For \( N \) equals \( N \), the system uses a leave-one-out (LOO) method. This approach trains on \( N-1 \) training samples and tests on the remaining one sample. The procedure is repeated until each data sample has been excluded from training and then used for testing [37].

\( N \)-fold cross validation has been used in several remote sensing applications. Brodley and Friedl used \( N \)-fold cross validation in conjunction with decision trees for the
mapping of land cover [59]. Kwak and Pedrycz used a wavelet decomposition method along with $N$-fold cross validation in a classification system for face recognition [60].
CHAPTER III

METHODOLOGIES

3.1 Introduction

The analysis of the effects of resolution variations on target detection accuracies was achieved using two case studies. In the first case study, a terrestrial vegetation dataset, namely Cogongrass-Johnsongrass, was used to determine at which resolution point(s) the Cogongrass and Johnsongrass could no longer be discriminated from one another. This also allowed for the demonstration of the system’s spectral-spatial 2D accuracy mapping capabilities.

In the second case study, an aquatic vegetation dataset, namely Water Hyacinth-American Lotus, was used to determine the same resolution boundaries as regarding the Cogongrass-Johnsongrass dataset. The Water Hyacinth-American Lotus dataset differed from the aforementioned dataset in that it included a temporal aspect that allowed for the demonstration of the spectral-spatial-temporal accuracy cube capabilities of the system.

Figure 3.1 shows a flow chart that depicts the main modules of the system. It can be noted from the figure that there are six different analysis paths that the system implements. Though it is not shown on the figure, it should also be mentioned that the “Spectral Downsampling” and “Spatial Pixel Mixing” blocks involve iterative processes.
Figure 3.1  Block Diagram of Spectral-Spatial-Temporal Classification System
3.2 Data Collection

The data was collected via an Analytical Spectral Devices (ASD) Fieldspec Pro handheld spectroradiometer, which captures individual hyperspectral signatures of a target in question. The device has a spectral range of 350 – 2500 nm, spectral resolution of 3 nm @ 700 nm and 10 nm @ 1400 - 2100 nm, and uses a single 512 element silicon photodiode array for sampling 350 - 1000 nm and two separate, graded index Indium-Gallium-Arsenide photodiodes for the 1000 - 2500 nm range [61]. The device was held approximately four feet above nadir when each Cogongrass-Johnsongrass measurement was taken and at leaf level when each Water Hyacinth-American Lotus reading was taken, and a 25° instantaneous field of view (IFOV) foreoptic was used to take all readings. The Cogongrass-Johnsongrass dataset consisted of 286 Cogongrass samples and 130 Johnsongrass samples collected at Eastman Farms on Artesia Road in Oktibbeha County, Mississippi. All samples were collected within +/- 2 hours of solar noon over one weekend in August of 2004, and targets were not revisited. Thus, the dataset was not multitemporal and was used only to investigate spectral-spatial resolution trade-offs. The Water Hyacinth-American Lotus dataset consisted of sample data collected approximately once every week from open-air vegetation tanks at the North Farm site of Mississippi State University. The data for these dates were combined to create monthly datasets for July, August, September, and October, 2005, giving 74 total data samples per species. Thus, this dataset was used to investigate spectral-spatial-temporal resolution tradeoffs.
3.3 Variation of Spectral Resolution

In order to study the effects of resolution variation upon our two-class problem, spectrally-reduced datasets had to be created. Hyperspectral signatures with approximately 1nm resolution per spectral band were used to create lower spectral resolution datasets. The spectral resolution of these high resolution signatures was reduced using an averaging filter. The data was subjected to a moving average, which was used to average a progressive number of samples, $N$, where $N$ represents the given level of downsampling. The resulting averaged sample was then placed in its appropriate position in the final dataset for that given $N$. For example, if $N = 30$, the first 30 samples of the original dataset would be averaged. The resulting data sample would be the first data sample of the respective downsampling dataset. Beginning with data sample 31, the next 30 data samples of the original dataset would be averaged, with the result being the second data sample of the downsampling dataset. This process would be repeated until all the original data samples had been used. Thus a new downsampling dataset would be created.

Datasets were simulated for each of the following levels of spectral resolution, or in this case reduction, since the original test data was high spectral resolution: $[1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9 \ 10 \ 20 \ 30 \ 40 \ 50 \ 60 \ 70 \ 80 \ 90 \ 100 \ 200 \ 300 \ 400 \ 500 \ 600 \ 700 \ 800 \ 900 \ 1000]$. A level of 1 indicates the spectral resolution is at the original full resolution. A level of $L$ indicates that the spectral resolution was reduced by a factor of $L$, and that the resulting spectral resolution is $1/L$ that of the original dataset. It can be seen that the levels of spectral resolution decrease in a sort of logarithmic fashion. It is necessary to note that
spectral resolution can be viewed in many ways, such as the number of bands in a signal, the spectral sampling period (separation between adjacent band center points), the FWHM, or 2 times the FWHM (if accounting for Nyquist Theory). In this thesis, the spectral resolution is defined as the FWHM. That is, the sampling period and the FWHM are equivalent.

Satellite sensor profiles were employed to simulate the resolutions of known satellite sensors. In essence, this was a very specialized form of varying the spectral resolution. The following satellite sensors were simulated: Advanced Land Imager (ALI), Compact Airborne Spectrographic Imager (CASI), GeoVantage (GEO), Hyperion (HYP), IKONOS, Regional Data Assembly Center Sensor (RDACS), TRW Imaging Spectrometer (TRWIS) 2, TRWIS B, and TRWIS D. The sensors and their respective spectral information can be seen in Table 3.1 [7,9,62-66]. It should be noted that all sensor profile modulation transfer functions were separately simulated using Gaussian distributions with the appropriate number of bands, band center points, FWHM’s and spectral ranges for each sensor, with the exception of the ALI and Hyperion sensors. For those sensors, the actual modulation transfer function was employed.
Table 3.1 Satellite Sensor Spectral Characteristics

<table>
<thead>
<tr>
<th>Satellite Sensor</th>
<th>Spectral Resolution (≈nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASI</td>
<td>2</td>
</tr>
<tr>
<td>TRWIS D</td>
<td>2</td>
</tr>
<tr>
<td>TRWIS 2</td>
<td>2</td>
</tr>
<tr>
<td>TRWIS B</td>
<td>5</td>
</tr>
<tr>
<td>HYP</td>
<td>10</td>
</tr>
<tr>
<td>RDACS</td>
<td>10</td>
</tr>
<tr>
<td>ALI</td>
<td>20 – 270</td>
</tr>
<tr>
<td>IKONOS</td>
<td>66 – 96</td>
</tr>
<tr>
<td>GEO</td>
<td>80 – 100</td>
</tr>
</tbody>
</table>

3.4 Variation of Spatial Resolution

Variation of the spatial resolution was achieved via simulated pixel mixing. The original data was collected so that each data sample is a pure endmember, in which case spatial resolution is considered to be “ideal.” This “ideal” data was then used to create lower spatial resolution datasets by mixing endmembers appropriately. Ten different levels of spatial resolution were simulated, with each level representing a different percentage of target presence within a pixel. For example, level 1 provided a pixel that was 10% target, level 5 gave a pixel which was 50% target, and so on.

In order to create these mixed pixel datasets, the data first had to be separated into usable datasets. After randomly sorting both datasets, $N$ samples of the target class and $2N$ samples of the non-target class were gathered. The non-target dataset was split in half so as to use the first half for mixing and the second half for a pure non-target dataset to use in classification. For each percentage of target presence, we created a new dataset in the following manner. First, the target dataset was multiplied times the decimal form of the required target percentage, which we will call $Pt$. Next, the non-target dataset was
multiplied times \(1 - Pt\). Finally, these two datasets were added together to create the new dataset. This process was repeated for target percentage levels of 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 percent. Figure 3.2 shows an illustrative example of the pixel mixing process.

![Representation of spatial pixel mixing process](image)

\[\text{Complete Pixel} = (\text{Nontarget} \times 0.3) + (\text{Target} \times 0.7)\]

Figure 3.2 Visual representation of spatial pixel mixing process

As a result of the linear mixing process, the two classes are target (mixed target and nontarget spectral signatures) and nontarget (pure nontarget spectral signatures). This strategy was aimed at simulating small aggregated patches of the target invasive species within a large scene of the non-target native vegetation.
3.5 Classification and Testing Methods

Two different testing and classification approaches were implemented when analyzing each resolution combination of the data. Both of these approaches were selected for investigation for this thesis’s invasive species detection applications since they have been used in hyperspectral target detection applications in the past and have been shown to be useful.

The first approach began with feature extraction/optimization using the Best Spectral Bands approach (BSB). Feature reduction using LDA was employed. The extracted features were then subjected to JK testing, which takes a given dataset, randomly sorts it, and then takes one half to use as training data and leaves the other half to use as testing data. A ML classifier was then used to classify the features.

The second approach used the All Spectral Bands (ASB) method. This approach used every spectral band as a feature. No feature reduction of any kind was used. The features were used for training and testing via the LOO method, which iteratively trains on all but one sample and tests on the remaining sample until all samples have been left out and tested. A NM classifier was used to classify the features.

3.6 Classification Accuracy Maps

After classification is complete for all of the various combinations of spatial, spectral, and temporal resolutions, the classification accuracies are stored in a 3D data cube. This data cube can be sliced according to user-specified parameters regarding the spectral, spatial, or temporal resolutions. The final result is a 2D resolution map showing the achieved system classification accuracies for the chosen resolution level. Figure 3.3
shows a conceptual illustrative example of the types of resolution maps available from the data cube.

Figure 3.3  Conceptual diagram of resolution data cube slicing
CHAPTER IV

RESULTS

4.1 Cogongrass-Johnsongrass

Results for the Cogongrass-Johnsongrass dataset are quite interesting. Overall classification accuracies remain relatively high for relatively poor spectral and spatial resolutions. Consider the classification accuracies for the BSB approach as shown in Figure 4.1. The overall classification accuracy is approximately 80% when the spectral resolution is 50nm FWHM and the target abundance is 50%. Also, note that when the target abundance is 90%, the overall classification accuracy is generally above 90% when the spectral resolution is from 50nm to 200nm FWHM. A very interesting result is that the classification accuracies tend to increase when the hyperspectral signature’s spectral resolution is slightly degraded. That is, as the spectral resolution decreases slightly, e.g., the FWHM increases from 1nm to 10nm, the classification accuracies tend to increase. The accuracies remain high for a while (e.g., 50nm to 100nm for 50% target abundance) and then begin to decrease again. The range over which the accuracies increase, remain relatively high, and then begin to decrease depends on the spatial resolution, i.e., the target abundance. In general, when the spectral resolution is between 10nm and 100nm, the classification accuracies are their highest, particularly when the target abundance is greater than 50%. These results indicate that a certain level of spectral smoothing actually increases our ability to utilize the hyperspectral data for discriminating between
Figure 4.1 Overall Cogongrass-Johnsongrass classification accuracies for the BSB approach
the targets and nontargets. Next, consider the classification results from the ASB approach for the Cogongrass-Johnsongrass dataset, as shown in Figure 4.2. Note that the highest classification accuracies achieved, regardless of spectral or spatial resolution, is around 75%. These accuracies are significantly lower than those for the BSB approach. This is to be expected since the ASB approach is much simpler than the BSB approach. Like the BSB results, there tends to be a region in the 60nm to 100nm FWHM range of spectral resolutions where relatively high classification accuracies are achieved. Also, a certain level of spectral smoothing, up to 3nm FWHM in this case, actually increases the classification accuracies. However, unlike the BSB results, there appear to be three spectral resolutions that achieve significantly higher classification accuracies than the other spectral resolutions; these are the 30nm, 500nm, and 800nm FWHM’s. The 500nm and 800nm FWHM cases are particularly interesting.

These spectral-spatial maps can be used to predict how certain sensors with known spectral resolutions are likely to behave. An example of this type of prediction map is shown in Figure 4.3, where the potential accuracies of the CASI, Hyperion, and TRWIS B sensors based on a spectral range from 350nm – 2500nm are seen. The prediction map shows that the accuracies of these sensors should be very high for pure target pixel, i.e., pixels with target abundances of 100%.

The overall Cogongrass-Johnsongrass classification accuracies for the simulated sensor profiles using the BSB and ASB approaches are shown in Figure 4.4. Results for the sensor profiles are generally as expected, with sensors having higher spectral resolutions performing with higher classification accuracies for the BSB method. As
Figure 4.2  Overall Cogongrass-Johnsongrass classification accuracies for the ASB approach
Figure 4.3  Spectral-spatial map showing sensor performance predictions for the CASI, Hyperion, and TRWIS B sensors.
Figure 4.4 Classification accuracies for the BSB and ASB approaches for the sensor profiles of the Cogongrass-Johnsongrass dataset
predicted by the sensor prediction map the separately simulated profiles of the CASI, Hyperion, and TRWIS B sensors perform the best, with accuracies of approximately 96%, while the IKONOS and GEO sensors perform the worst, with accuracies of approximately 60%. These results are to be expected since the IKONOS and GEO sensors are designed such that the spectral resolution is very low in order to trade off to have a much higher spatial resolution. The results for the ASB approach show the classification accuracies to fluctuate slightly, but generally tend to stay around the 60-65% range.

4.2 Water Hyacinth-American Lotus

Results for the Water Hyacinth-American Lotus dataset are also quite interesting. Temporally-layered spectral-spatial mapping schemes showing the overall Water Hyacinth-American Lotus classification accuracy trends for the BSB and ASB approaches can be seen in Figures 4.5 and 4.6, respectively. For the BSB approach, overall classification accuracies increase as spatial resolution increases. However, the classification accuracies are shown to actually decrease as the spectral resolution increases. For the months of August, September, and October, this occurs even when the target abundance is very low, around 10% to 20%. In fact, for these cases, the classification accuracies reach approximately 90% when the spectral resolution is approximately 9nm to 90nm FWHM. These results are quite unexpected. It can be seen from the figures that, for the BSB method, July gives the worst accuracies while October seems to give the best.
Figure 4.5  Overall classification accuracies for the BSB approach using 2D spectral-spatial maps for the Water Hyacinth-American Lotus dataset
Figure 4.6 Overall classification accuracies for the ASB approach using 2D spectral-spatial maps for the Water Hyacinth-American Lotus dataset
For the ASB method, trends within the classification accuracies, relative to spectral and spatial resolutions, are much more predictable as compared to the BSB approach. For target abundances of 60% or higher, the classification accuracies remain high across the full range of spectral resolutions. However, when the target abundance is 30% or lower, the accuracies are very low regardless of the spectral resolution. As with the Cogongrass-Johnsongrass case, there appear to be isolated spectral resolutions that achieve relatively higher classification accuracies. These cause vertical striations to appear in the accuracy maps. For example, within the month of September, a vertical striation appears at the spectral resolution of 500nm FWHM. In fact, relatively high classification accuracies are achieved even with the target abundance is only 30%. For the ASB approach, while the accuracies are generally the same across time, the month of October seems to give high accuracies at more resolution combination levels.

Other interesting results can be seen in the additional 2D mapping schemes for the different testing methods. These mapping schemes are shown in Figures 4.7 – 4.10. It can be seen from the spatial-temporal resolution maps that, for both the ASB and BSB approaches, classification accuracies within each month tend to increase as spatial resolution increases, with the highest accuracies for the BSB approach being achieved by holding the spectral resolution constant at lower resolutions. For the ASB testing method, monthly classification accuracies are more evenly distributed throughout the spectral resolutions.

The spectral-temporal resolution maps show that, for the BSB method, classification accuracies tend to decrease as spectral resolution increases. This is similar
Figure 4.7 Overall classification accuracies for the BSB approach using 2D spatial-temporal maps for the Water Hyacinth-American Lotus dataset
Figure 4.8 Overall classification accuracies for the ASB approach using 2D spatial-temporal maps for the Water Hyacinth-American Lotus dataset
Figure 4.9  Overall classification accuracies for the BSB approach using 2D spectral-temporal maps for the Water Hyacinth-American Lotus dataset
Figure 4.10 Overall classification accuracies for the ASB approach using 2D spectral-temporal maps for the Water Hyacinth-American Lotus dataset.
to the trend shown by the spectral-spatial resolution maps in Figure 4.5. Again, the ASB testing method tends to give more evenly distributed classification accuracies across the entire spectral range. For both the ASB and BSB approaches, classification accuracies increase as the constant spatial resolution increases.

Sensor profile results for the Water Hyacinth-American Lotus case study are similar to those of the Cogongrass-Johnsongrass case study. The BSB results for each case study seem to follow the same general “sensor accuracy trend,” despite the fact that the accuracies achieved are much higher overall. Several sensors, including the ALI, CASI, and TRWIS sensors, achieve accuracies of 100%, while the lowest accuracy, obtained by the RDACS sensor, is around 85%.

The ASB testing method seems to show the same kind of fluctuating trend in both case studies; however, the fluctuation in the Water Hyacinth-American Lotus case study is much greater, with accuracies falling within the range of 45-95%. The ALI, Hyperion, and TRWIS2 sensors achieve accuracies in the range of 85-95%, while the remaining sensors yield accuracies in the lower range of 45-65%. The overall Water Hyacinth-American Lotus classification accuracies for the simulated sensor profiles using BSB and ASB approaches are shown in Figures 4.11 and 4.12, respectively.
Figure 4.11 Classification accuracies for the BSB approach for the sensor profiles of the Water Hyacinth-American Lotus dataset.
Figure 4.12  Classification accuracies for the ASB approach for the sensor profiles of the Water Hyacinth-American Lotus dataset
CHAPTER V
CONCLUSIONS

5.1 Review

For this study, hyperspectral data for two target-nontarget case studies, namely, Cogongrass-Johnsongrass and Water Hyacinth-American Lotus, were used to investigate the trade-offs involved with varying spectral, spatial, and temporal resolutions. Two target detection approaches, BSB and ASB, were used to demonstrate the effects of the resolution combinations. Conclusions drawn from the results of each case study are as follows.

5.2 Cogongrass-Johnsongrass

It can be seen that, for the Cogongrass-Johnsongrass dataset, classification accuracies typically behave as expected. For the BSB approach, accuracies are seen to generally increase as spectral and spatial resolutions increase. The fact that a small amount of spectral reduction actually improves the overall classification accuracy is likely due to the fact that the averaging filter used to spectrally reduce the data tends to act like a lowpass filter. This “lowpass filtering” helps to “improve” the dataset by smoothing out high-frequency noise that is generally present in hyperspectral data. This shows that, when dealing with hyperspectral data, a certain amount of spectral smoothing can be desirable for use in obtaining higher classification accuracies. The fact that
relatively high classification accuracies can be achieved by employing relatively low spectral-spatial resolution combinations shows that it is not necessary to use sensors with the highest possible resolutions in order to gain satisfactory results. In a way, this could be viewed as being cost-effective, since sensors with better resolutions typically cost more.

For the ASB approach, the overall classification accuracies tend to increase as spatial resolution increases across the entire spectral resolution range. When compared to the BSB approach, the much lower overall accuracies of the ASB method are expected, since the latter is much less complex in nature. The high-accuracy striations seen in the spectral-spatial resolution maps give the idea that there are unique characteristics involved with certain spectral resolutions that lend themselves to achieving higher classification accuracies. Similar to the results of the BSB method, it can also be seen that a slight amount of spectral smoothing tends to give higher classification accuracies for higher target abundances.

In the end, if one were to use the spectral-spatial resolution accuracy maps to determine an optimum sensor specification for this application, the following could be concluded:

- High target detection accuracies can be achieved when using a best spectral band feature extraction, LDA feature reduction, and ML classification. These accuracies are typically 90% or higher when the spectral resolution is in the range of 5nm to 100nm FWHM and the target abundance is 90% to 100%. That is, the spatial resolution of the sensor is
high enough such that any aggregated patch of the target invasive vegetation is large enough to constitute 90% to 100% of the pixel. Likewise, the accuracies are typically 80% or higher when the target abundance is 70% to 100%.

- Moderate target detection accuracies can be achieved when using the simplistic “all spectral band” approach, i.e., no spectral feature extraction, no feature reduction, and a NM classifier. These accuracies are greater than 70% for specific spectral resolutions, namely 30nm, 500nm, and 800nm, when the target abundance is 80% to 100%. For these spectral resolutions, the classification accuracies remain at around 65% even when the target abundance decreases to approximately 40%.

The results for the sensor profiles are also as expected, with higher accuracies being achieved by sensors with higher spectral resolutions, such as the CASI, TRWIS B, and Hyperion sensors. However, it should be noted that these results are based on spectral features alone. That is, vicinal information or spatial features, such as textures within an image, are not utilized, so the analysis does not take advantage of the higher spatial resolutions of some of the sensors, such as IKONOS and GeoVantage.

5.3 Water Hyacinth-American Lotus

For the Water Hyacinth-American Lotus dataset, classification accuracies for the BSB approach show that, while the overall classification accuracies generally increase as spatial resolution increases, an apparent inverse characteristic of the classification accuracies with respect to the spectral resolution seems to occur. This is likely due to the
fact that the system is being over-trained at high resolutions. As previously mentioned, the Water Hyacinth-American Lotus dataset consists of only 74 samples of each species. The BSB method uses half of those samples for training and the other half for testing. The end result is that 37 samples of each species are being trained using anywhere from 500 – 2000 features at the higher spectral resolution levels. According to the $10n$ rule, the maximum allowable number of features that should be used in a classification system is $10n$ samples. In this case, the maximum number of allowable features should be 370. Increasing the number of features beyond this limit leads to a reduction in classification accuracies, an occurrence known as Hughes phenomenon [67]. The averaging that is done to reduce the spectral resolution of the data results in an increasingly lower number of features. Thus, as the spectral resolution is reduced, the $10n$ rule is more closely adhered to, and the overall classification accuracies increase.

For the ASB approach, overall classification accuracies tend to be evenly distributed over the entire spectral range and are seen to generally increase as spatial resolution increases. The very surprising result that the classification accuracies are extremely high is likely due to the fact that the original data was of very good quality. As in the Cogongrass-Johnsongrass case study, high-accuracy striations can be seen in spectral-spatial resolution maps. This again implies that there are qualities about certain spectral resolutions that are conducive to attaining higher classification accuracies.

Analysis of the spectral-temporal and spatial-temporal resolution maps confirms that the classification accuracies generally behave as expected with regard to the spatial resolution. Classification accuracies generally increase as spatial resolution increases.
However, similarly to the trend shown in the spectral-spatial resolution maps for this case study, classification accuracies tend to decrease as spectral resolution increases. Again, this is likely due to the aforementioned Hughes phenomenon. It can be seen that the use of the addition resolution maps can be very helpful in determining the classification accuracy trends of a given dataset more acutely.

For this particular application, if one were to use the resolution accuracy maps to determine an optimum sensor specification, the following could be concluded:

- High target detection accuracies can be achieved when using a best spectral band feature extraction, LDA feature reduction, and ML classification. These accuracies are typically 90% or higher when the spectral resolution is in the range of 90nm to 1000nm FWHM and the target abundance is 50% to 100%. That is, the spatial resolution of the sensor is high enough such that any aggregated patch of the target invasive vegetation is large enough to constitute 50% to 100% of the pixel. Likewise, the accuracies are typically 80% or higher when the target abundance is 30% to 100%.

- High target detection accuracies can be achieved when using the simplistic “all spectral band” approach, i.e., no spectral feature extraction, no feature reduction, and a NM classifier. These accuracies are generally 90% or higher for all spectral resolutions when the target abundance is 60% to 100%. The classification accuracies remain at around 70% even when the target abundance decreases to approximately 20%.
• High target detection accuracies can be achieved for the months of July –
October. The highest classification accuracies are generally found in the
months of August and September, while the lowest classification
accuracies are found in the month of July. However, all months resulted
in high accuracies.

The results of the sensor profiles seem to behave similar to those in the
Cogongrass-Johnsongrass case study, with the exception that the profile results for the
Water Hyacinth-American Lotus case study have much more variation, with the lower
accuracies of the CASI, TRWIS B, and other sensors possibly due to overtraining the
system.

5.4 Overall System Performance

The classification system that has been developed is effective in determining what
spectral and spatial resolution reductions are acceptable before classification accuracies
are unacceptably affected. Spectral-spatial resolution accuracy maps are effective ways
for individuals and/or companies to choose or design sensors based on given accuracy or
resolution constraints. The ability to use temporal data to create and slice a data cube
provides for the additional ability of an individual and/or company to account for the time
of year when choosing or designing their sensor(s).

Results of the classification system show that Hughes phenomenon unequivocally
plays a part in how classification accuracies behave. This is especially seen in accuracies
with regard to spectral resolutions, effectively forcing a user to provide this classification
system with ample amounts of training data. The outstanding results of the Water
Hyacinth-American Lotus case study versus the good results of the Cogongrass-Johnsongrass case study heavily imply that the quality of results obtained is directly dependent on the quality of the data provided.

It should also be noted that, for this system, since the spatial resolution varies with regard to target abundance within a pixel, sensors should be designed and/or selected with target size in mind. For example, if the results of a particular dataset give 90% classification accuracies with 70% target abundance, a sensor with 100m x 100m spatial resolution must have a target that occupies at least 70% of its pixel size if those 90% classification accuracies are to be obtained.
CHAPTER VI

FUTURE WORK

Future work with this classification system would likely mainly involve expansion of the options given to the user when slicing the data cube. For example, the system could be updated to include an option for merging data contained with a given spectral, spatial, or temporal range. Also, other system expansions could include additional analysis techniques and approaches, such as nearest neighbor (NN) classification, principal component analysis (PCA), wavelet-based feature extraction, data fusion, and confidence interval application and visualization.

At this point, the temporal resolution in the system simply refers to the time of year that the data is collected. Varying the temporal resolution to simulate different revisit times to a target could be included within this system, as well as the added dimension of varying the radiometric resolution. System functionality could also be modified by including the use of Gaussian distributions rather than uniform distributions for simulating the varying FWHM’s used by the classification system. Additionally, the sensor profiles could be adapted to include some type of noise to simulate atmospheric conditions.

Another addition to this system could involve different input data types. For example, the system could be modified to accept hyperspectral imagery as input data. In
this case, the testing and classification system could be further modified to take into account spatial and vicinal information, such as textures.
REFERENCES


[62] M. Pritchard, NERC Earth Observation Data Centre, [Online]. Available: [http://www.neodc.rl.ac.uk/?option=displaypage&Itemid=71&op=page&SubMenu=-1](http://www.neodc.rl.ac.uk/?option=displaypage&Itemid=71&op=page&SubMenu=-1)


