Hyperspectral Remote Sensing

UNIT-IV

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Data Cubes and Spectral Vectors

A spectral cube is a three-dimensional array containing spatial (image) information on the *x* and *y* axes and spectral information on the *z* axis. Individual spectra, spectral maps, and full spectral cubes can be created from a single spectral cube.

Spectral cubes display different stratified, graphical thicknesses in a three-dimensional perspective that can be a useful tool for overall image analysis.

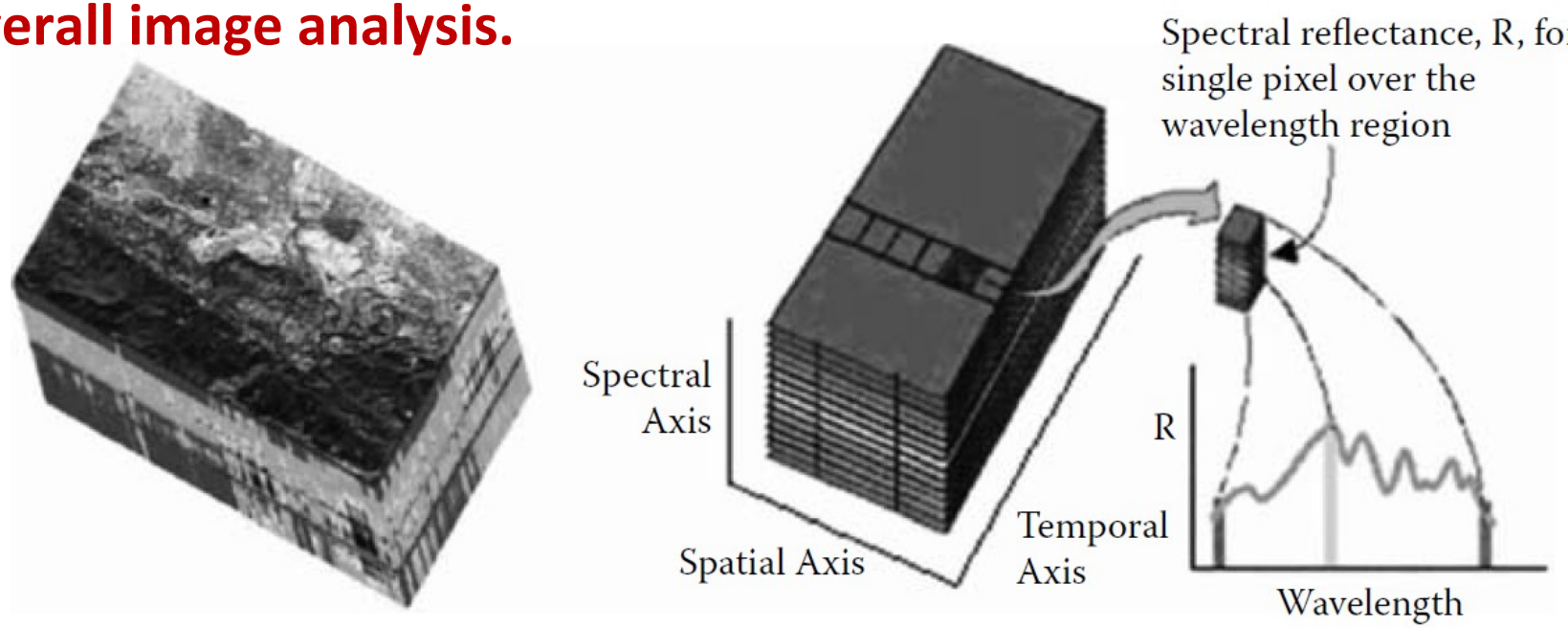


Figure 5.6 Spectral cube and the fundamental components.

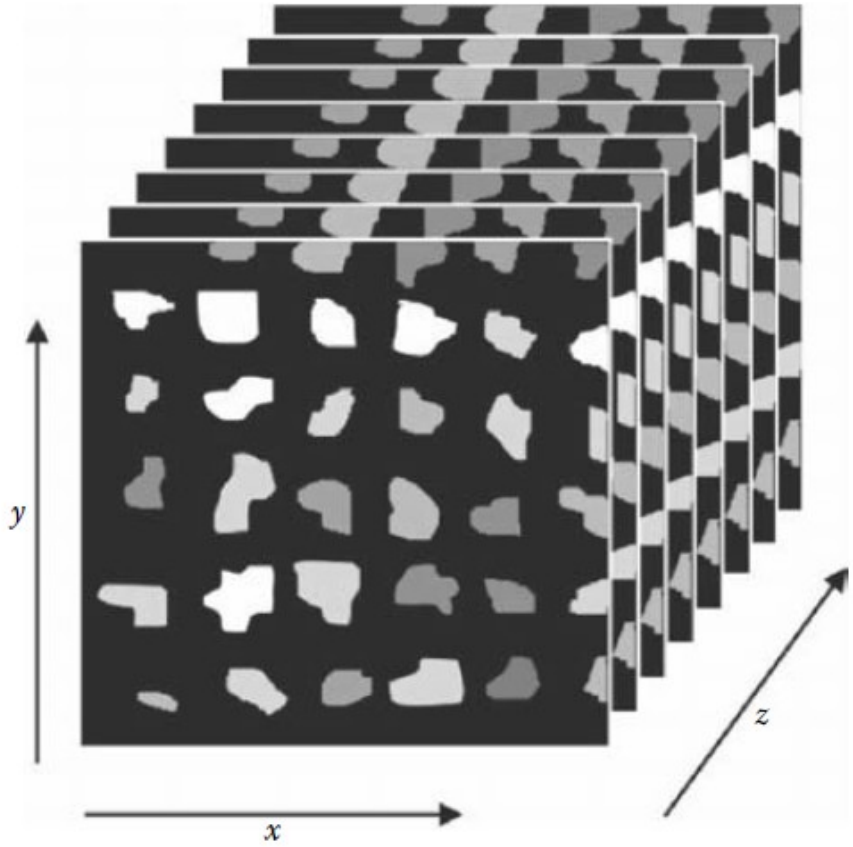


Figure 5.7 A typical image cube generated by a hyperspectral imager, with two spatial dimensions x and y, and one spectral dimension z.

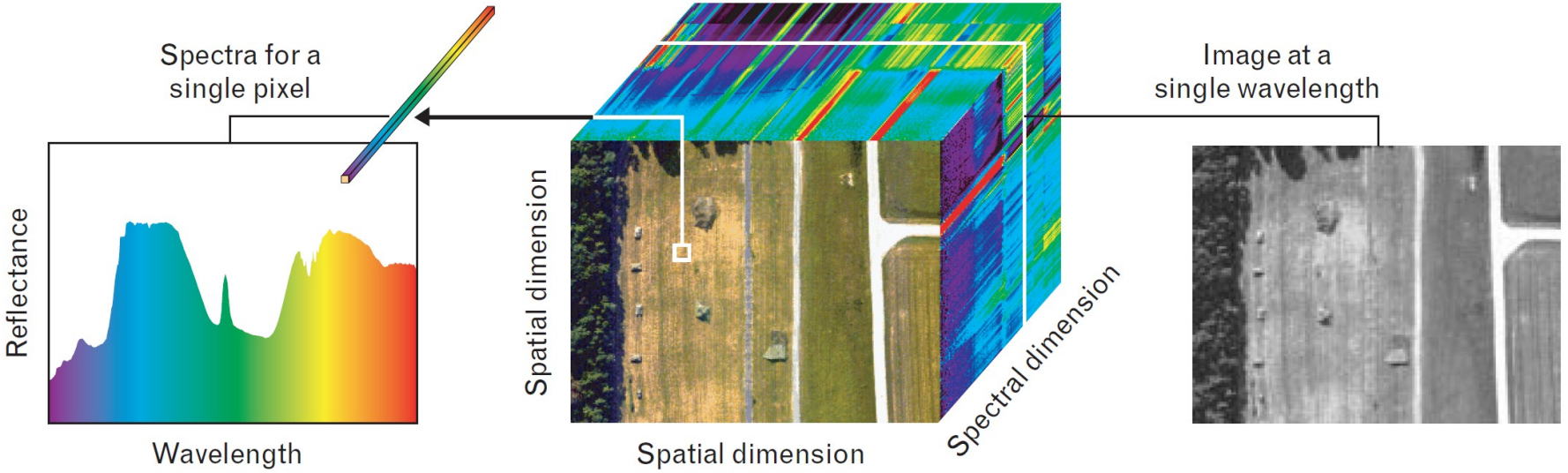
As a result of spatial and spectral sampling, airborne hyperspectral imaging (HSI) sensors produce a three dimensional (3D) data structure (with spatial-spatial spectral components), referred to as a data cube.

The 3D Hypercube Display emphasizes the high spectral content of the hyperspectral image while allowing you to quickly examine any of the individual wavelength bands. The 3D Hypercube Display window portrays the hyperspectral image as a three-dimensional "image cube".

If we extract all pixels in the same spatial location and plot their spectral values as a function of wavelength, the result is the average spectrum of all the materials in the corresponding ground resolution cell

The values of all pixels in the same spectral band, plotted in spatial coordinates, result in a grayscale image depicting the spatial distribution of the reflectance of the scene in the corresponding spectral wavelength.

The top and right panels of the cube show the corresponding edge cells of each wavelength band, with wavelength increasing toward the back of the cube.



Basic data-cube structure (center) in hyperspectral imaging, illustrating the simultaneous spatial and spectral character of the data. The data cube can be visualized as a set of spectra (left), each for a single pixel, or as a stack of images (right), each for a single spectral channel

Spectral library

The spectral library is a collection of spectra of natural and man made materials.

These libraries provide a source of reference spectra of varieties of targets(minerals, rocks, vegetation species) for remote identification for these targets.

The relative distance between sensor and target does not affects the results of spectral library.

JHU(John Hopkins University) Laboratory

Minerals (0.4-15 micrometer)
Rocks (2-25 micrometer)

Manmade features (0.3-12.5 micrometer)
Lunar rock samples

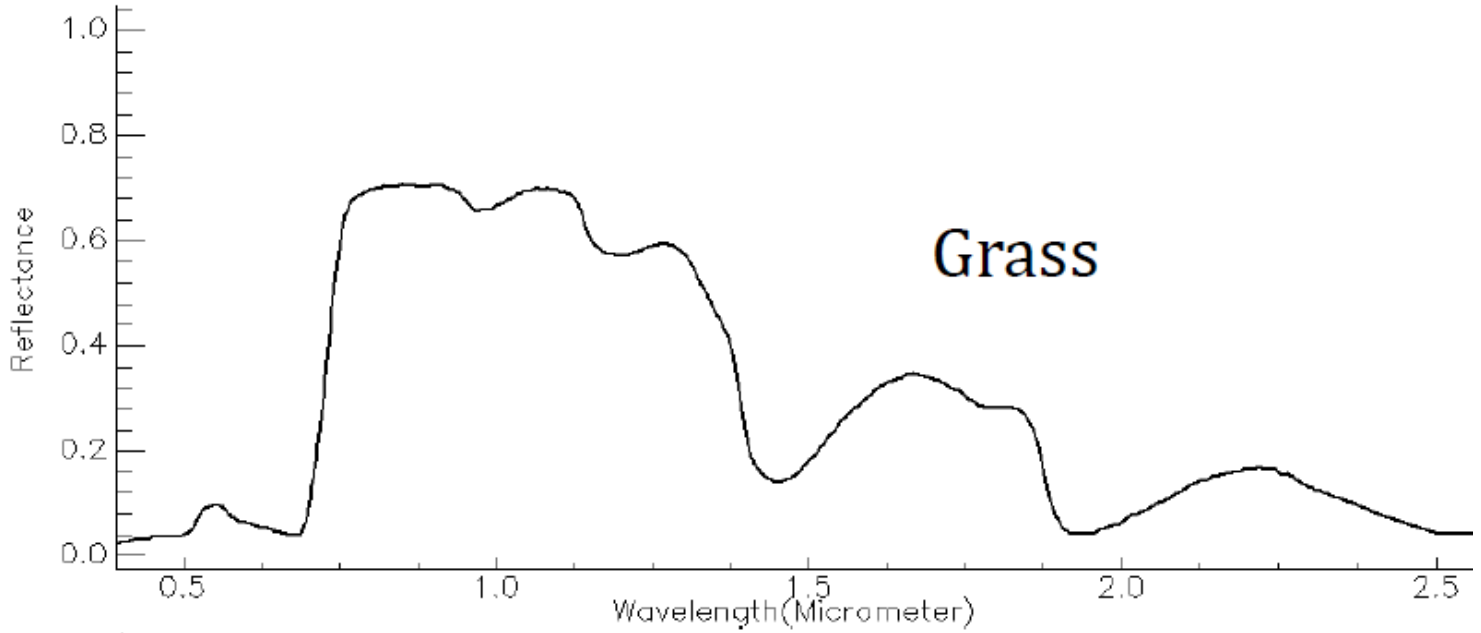
USGS_Vegetation laboratory
Vegetation (Visible-near infrared –shortwave domain)

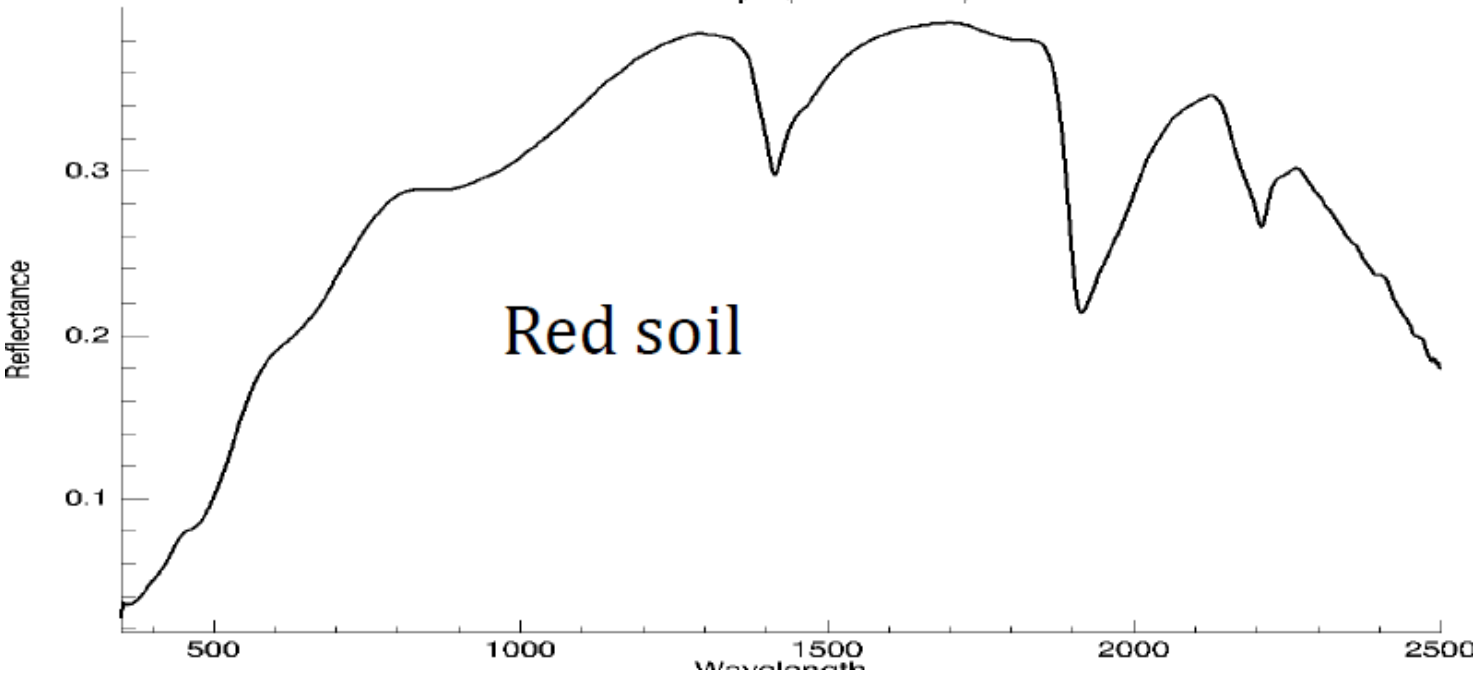
Jet propulsion laboratory for rocks and minerals

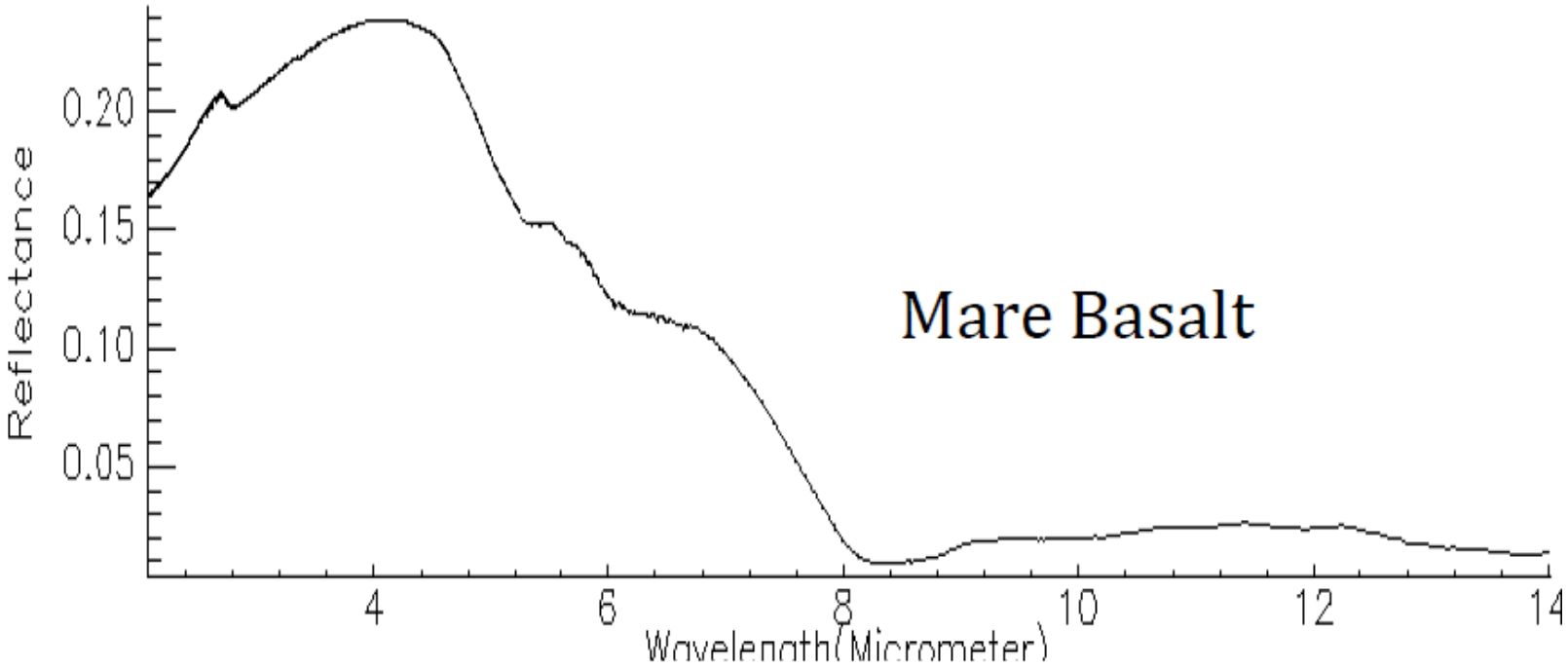
Minerals(Visible-near infrared –shortwave domain)

USGS(United States Geological Survey) Spectral laboratory

Minerals(Visible-near infrared –shortwave domain)
Rocks(Thermal domain)


Grass
Reflectance
1.0
0.8
0.6
0.4
0.2
0.0
0.5
1.0
1.5
2.0
2.5
Wavelength(Micrometer)


Red soil
Reflectance
0.3
0.2
0.1
500
1000
1500
2000
2500


Mare Basalt
Reflectance
0.20
0.15
0.10
0.05
4
6
8
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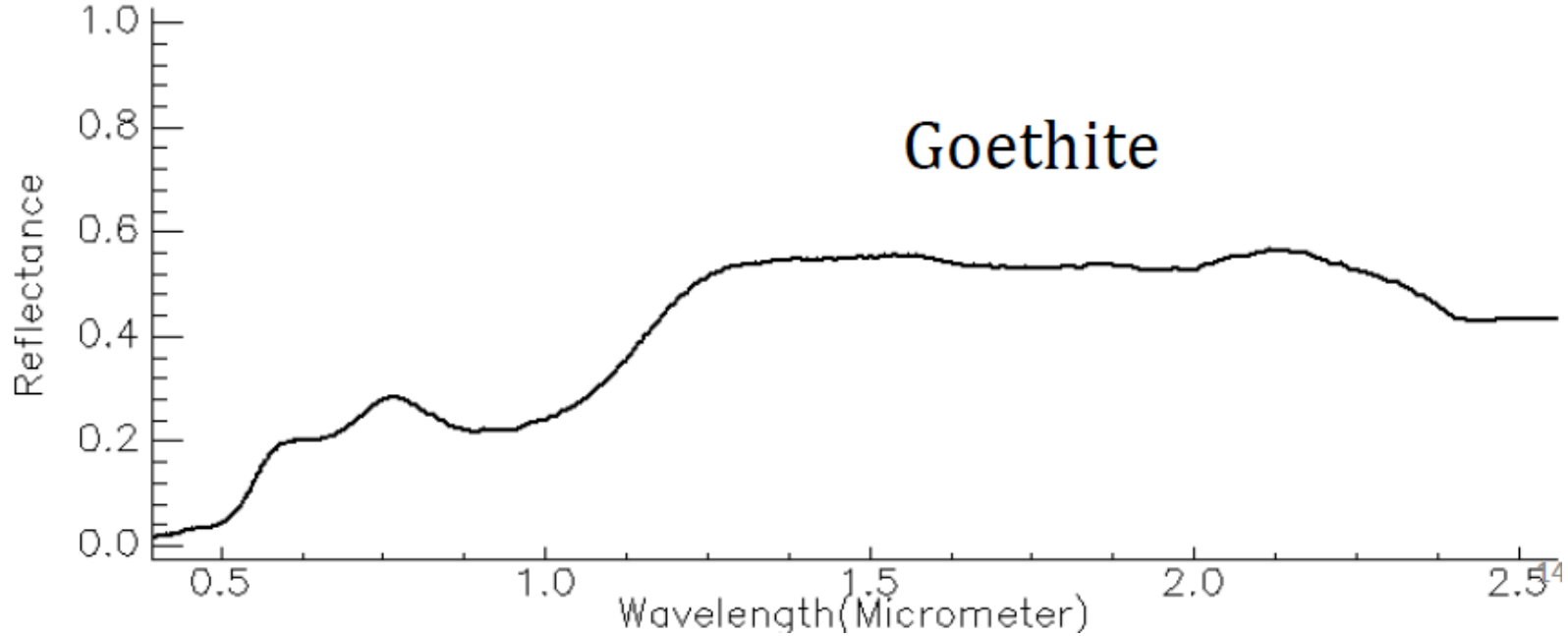
12
14
Wavelength(Micrometer)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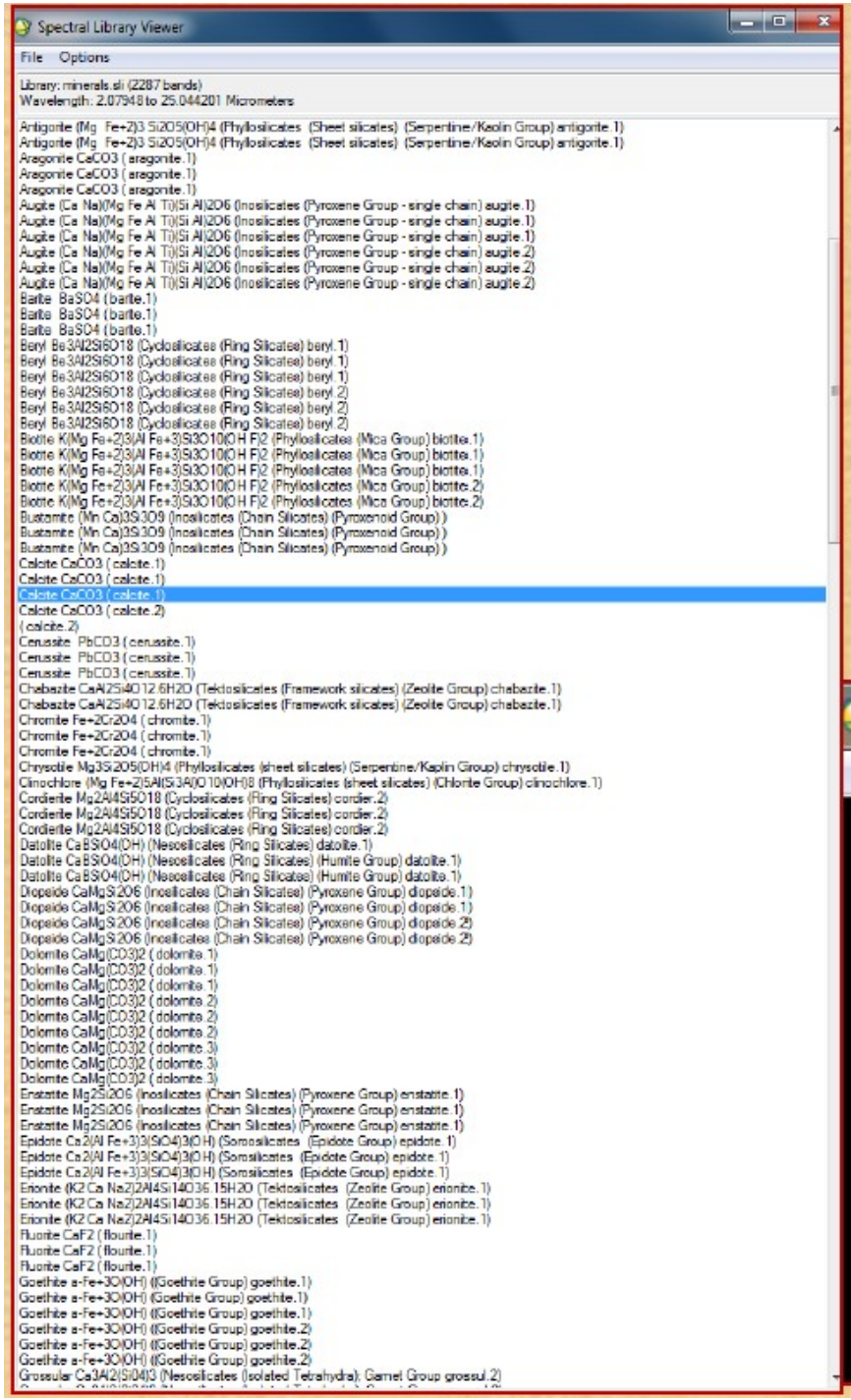
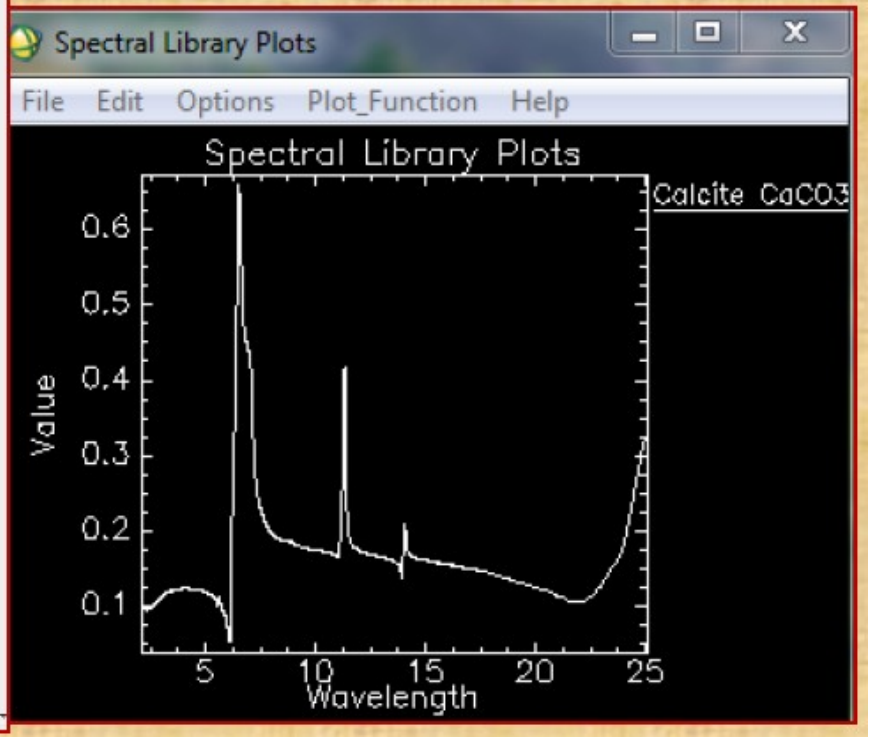
Wavelength(Micrometer)

JHU Spectral Library for Minerals

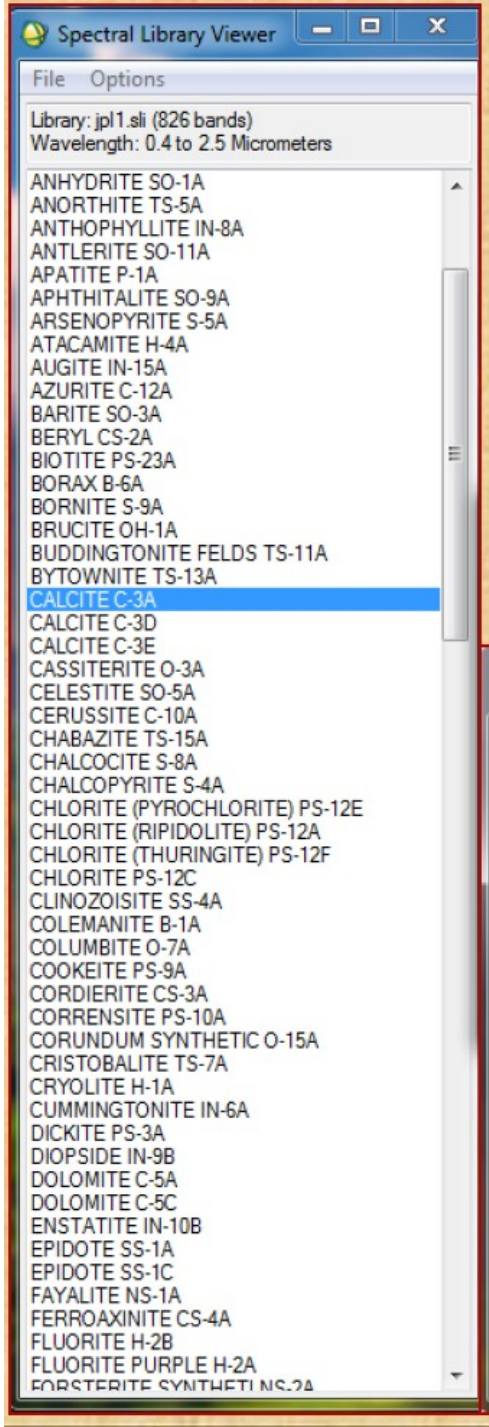
Wavelength: 2.07948 to 25.044201 Micrometers

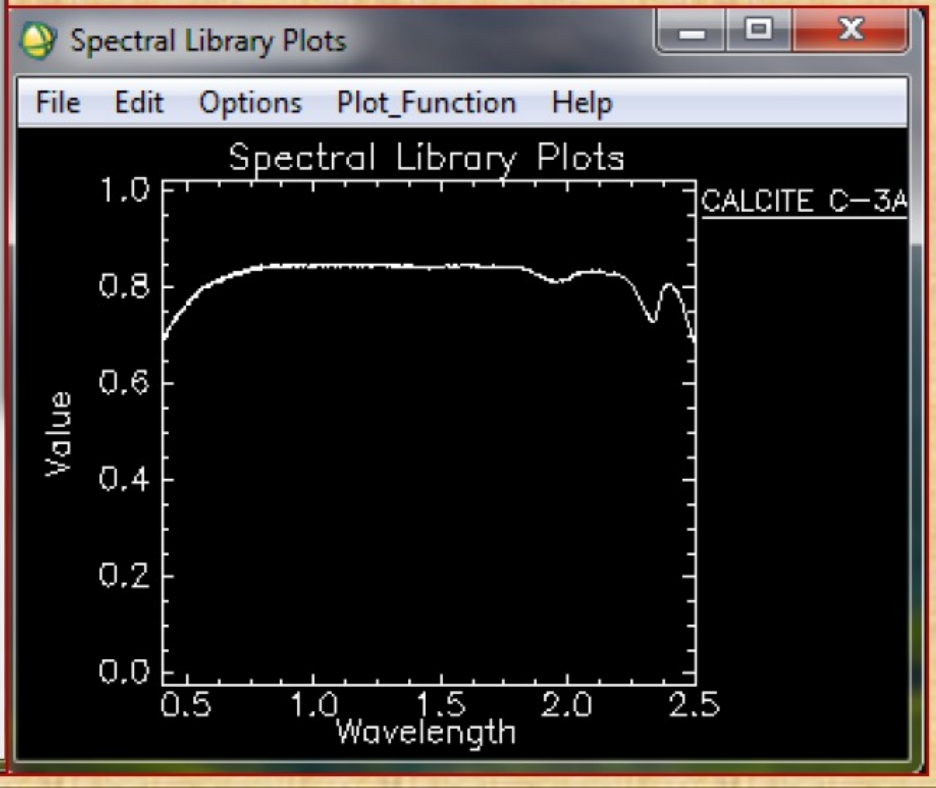


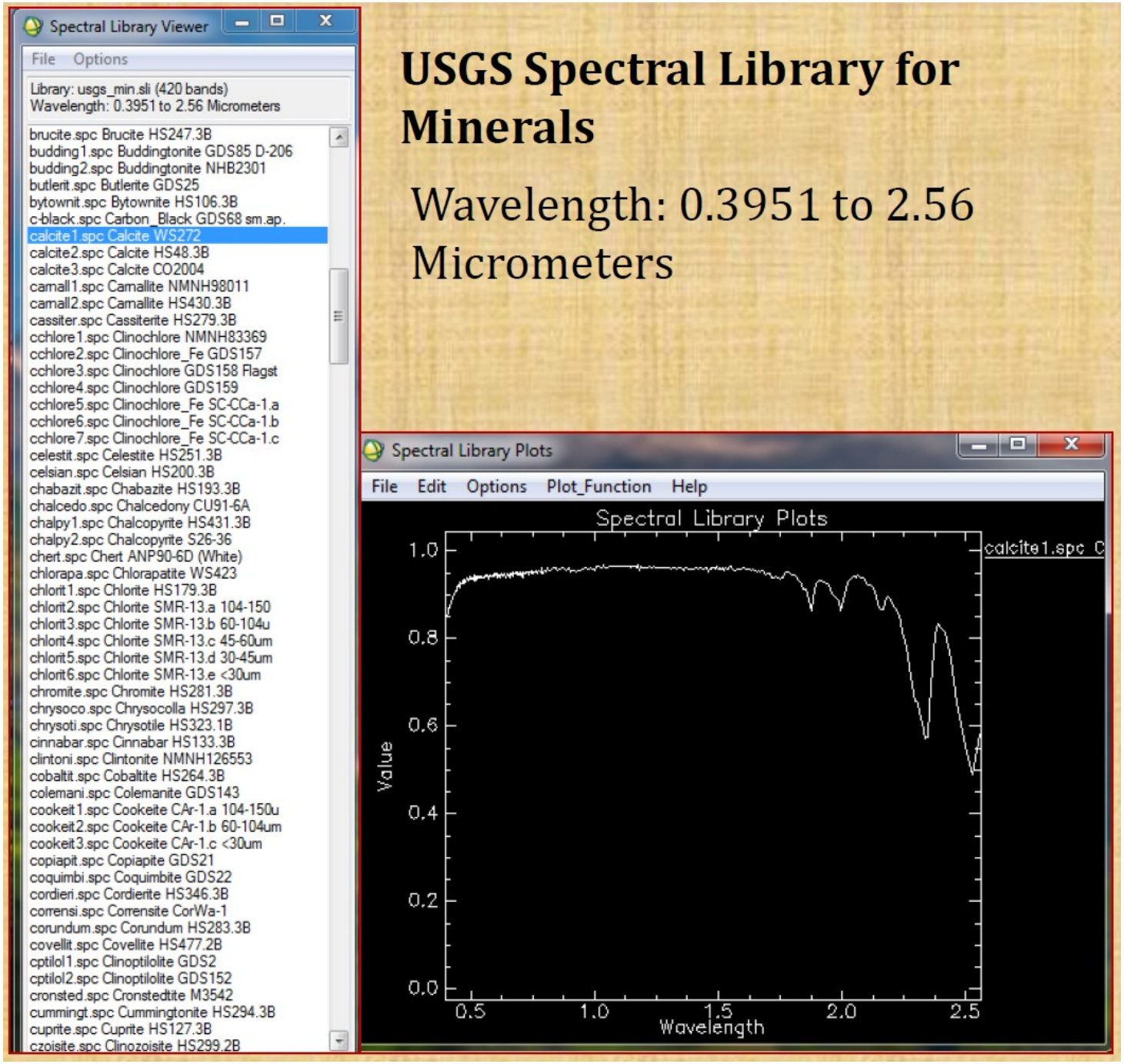


JPL Spectral Library for Minerals

Wavelength: 0.4 to 2.5 Micrometers






Spectral Library Viewer
File Options
Library: usgs_min.sli (420 bands)
Wavelength: 0.3951 to 2.56 Micrometers
brucite.spc Brucite HS247.3B
budding1.spc Buddingtonite GDS85 D-206
budding2.spc Buddingtonite NHB2301
butlerit.spc Butlerite GDS25
bytownit.spc Bytownite HS106.3B
c-black.spc Carbon_Black GDS68 sm.ap.
calcite1.spc Calcite WS272
calcite2.spc Calcite HS48.3B
calcite3.spc Calcite CO2004
carnall1.spc Carnallite NMNH98011
carnall2.spc Carnallite HS430.3B
cassiter.spc Cassiterite HS279.3B
cchlore1.spc Clinochlore NMNH83369
cchlore2.spc Clinochlore_Fe GDS157
cchlore3.spc Clinochlore GDS158 Flagst
cchlore4.spc Clinochlore GDS159
cchlore5.spc Clinochlore_Fe SC-CCa-1.a
cchlore6.spc Clinochlore_Fe SC-CCa-1.b
cchlore7.spc Clinochlore_Fe SC-CCa-1.c
celestit.spc Celestite HS251.3B
celsian.spc Celsian HS200.3B
chabazit.spc Chabazite HS193.3B
chalcedo.spc Chalcedony CU91-6A
chalpy1.spc Chalcopyrite HS431.3B
chalpy2.spc Chalcopyrite S26-36
chert.spc Chert ANP90-6D (White)
chlorapa.spc Chlorapatite WS423
chlorit1.spc Chlorite HS179.3B
chlorit2.spc Chlorite SMR-13.a 104-150
chlorit3.spc Chlorite SMR-13.b 60-104u
chlorit4.spc Chlorite SMR-13.c 45-60um
chlorit5.spc Chlorite SMR-13.d 30-45um
chlorit6.spc Chlorite SMR-13.e <30um
chromite.spc Chromite HS281.3B
chrysoco.spc Chrysocolla HS297.3B
chrysoti.spc Chrysotile HS323.1B
cinnabar.spc Cinnabar HS133.3B
clintoni.spc Clintonite NMNH126553
cobaltit.spc Cobaltite HS264.3B
colemani.spc Colemanite GDS143
cookeit1.spc Cookeite CAr-1.a 104-150u
cookeit2.spc Cookeite CAr-1.b 60-104um
cookeit3.spc Cookeite CAr-1.c <30um
copiapit.spc Copiapite GDS21
coquimbi.spc Coquimbite GDS22
cordieri.spc Cordierite HS346.3B
corrensi.spc Corrensite CorWa-1
corundum.spc Corundum HS283.3B
covellit.spc Covellite HS477.2B
cptilol1.spc Clinoptilolite GDS2
cptilol2.spc Clinoptilolite GDS152
cronsted.spc Cronstedtite M3542
cummingt.spc Cummingtonite HS294.3B
cuprite.spc Cuprite HS127.3B
czoisite.spc Clinozoisite HS299.2B
USGS Spectral Library for Minerals
Wavelength: 0.3951 to 2.56 Micrometers
Spectral Library Plots
File Edit Options Plot_Function Help
Spectral Library Plots
calcite1.spc C
Value
1.0
0.8
0.6
0.4
0.2
0.0
0.5
1.0
1.5
2.0
2.5
Wavelength

Importance of Spectral library development

Spectral signatures of minerals and few vegetation species are unique. Spectral features help in identifying the elements / targets.

Characterization of elements based on spectral signatures is rapid and reliable method.

Spectral profiles of elements (say rocks and minerals) should be preserved with every details (grain size and semi quantitative mineralogy etc.).

Spectral features are as reliable as any other semi quantitative chemical methods.

Reference for target detection-(Known to unknown)

Factors controlling the quality and information in spectra

External factors

- Properties of a spectrometer
- Wavelength within which measurements are being made
- BRDF(Influences the continuum of the spectral curve not the spectral feature)
- Intensity of incident radiation(Lamp used in lab or sun light)

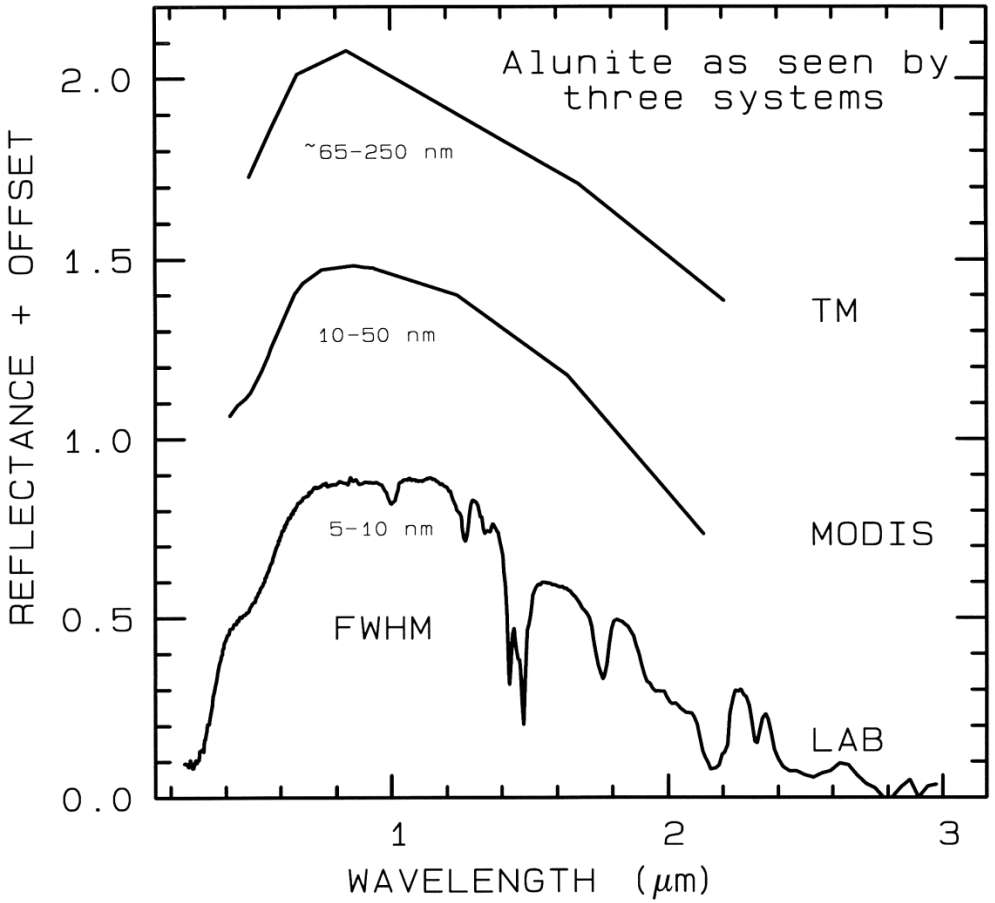
Target/Intrinsic Factors

Atomic processes operative in the target or sample.

Texture(Grain size etc.)

External Factors

Properties of a spectrometer



Parameters that describe the capability of a spectrometer:

(1) *Spectral range*

(2) *Spectral bandwidth*

(3) *Spectral sampling*,

(4) signal-to-noise ratio.

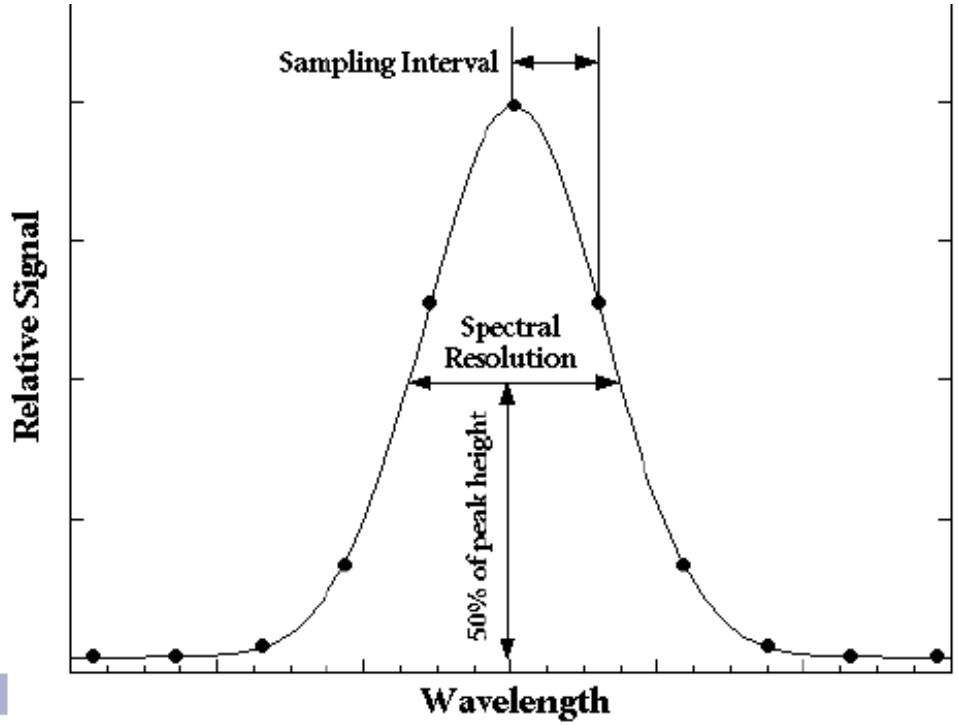
1) Spectral range: Spectral range is important to cover enough diagnostic spectral absorption to solve a desired problem. a) Ultraviolet (UV): 0.001 to 0.4 µm, b) visible: 0.4 to 0.7 µm, c) near-infrared (NIR): 0.7 to 3.0 µm, d) the mid-infrared (MIR): 3.0 to 30 µm, and d) the far infrared (FIR): 30 µm to 1mm

2) Spectral bandwidth: Spectral band width is the width of an individual spectral channel in the spectrometer. The narrower the spectral Bandwidth, the narrower the absorption feature the spectrometer will accurately measure.

3) Spectral sampling:

Spectral sampling is the distance in wavelength between the spectral band pass profiles for each channel in the spectrometer as a function of wavelength. The Nyquist theorem states that the maximum information is obtained by sampling at one-half the FWHM

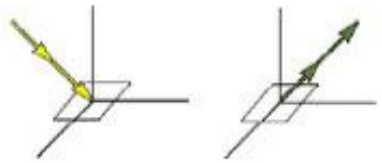
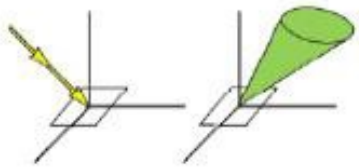
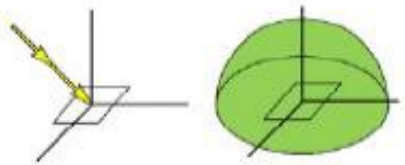
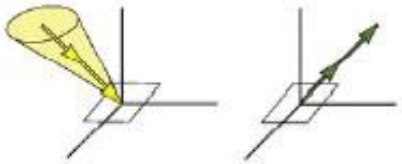
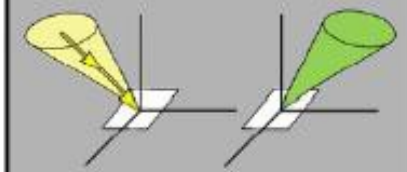
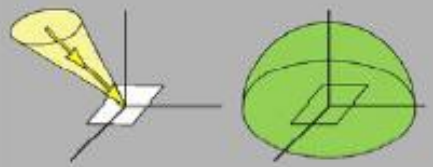
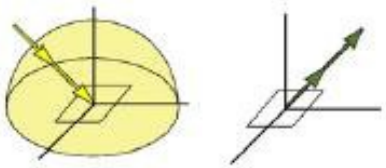
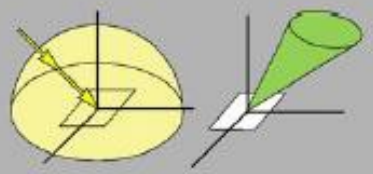
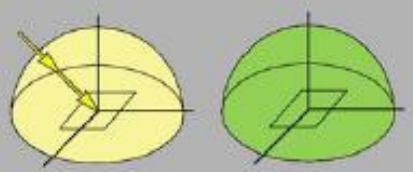
Spectral resolution: narrowest spectral features that can be resolved by a spectrometer(full width at half maximum FWHM)



4) signal-to-noise ratio (S/N). The S/N is dependent on the detector sensitivity, the spectral band width, and intensity of the light reflected or emitted from the surface being measured.

Bidirectional reflectance-distribution function (BRDF)

Bidirectional reflectance-distribution function (BRDF), a mathematical function "relating the irradiance incident from one given direction to its contribution to the reflected radiance in another direction "(Nicodemusetal.,1977). Importantly, BRDF was defined as a conceptual property of the surface, at infinitesimally small angles

Incoming/**Reflected**	**Directional**	**Conical**	**Hemispherical**
Directional	Bidirectional Case 1 	Directional-conical Case 2 	Directional-hemispherical Case 3 
Conical	Conical-directional Case 4 	Biconical Case 5 	Conical-hemispherical Case 6 
Hemispherical	Hemispherical-directional Case 7 	Hemispherical-conical Case 8 	Bihemispherical Case 9 

Wavelength domain for reflectance spectroscopic studies

a)Ultraviolet (UV): 0.001 to 0.4 µm,

b)visible: 0.4 to 0.7 µm,

c)near-infrared (NIR): 0.7 to 1.0 µm,

d)short-wave infrared(SWIR): 1.0 to 2.5 µm

e)the mid-infrared (MIR): 2.5 to 30 µm,

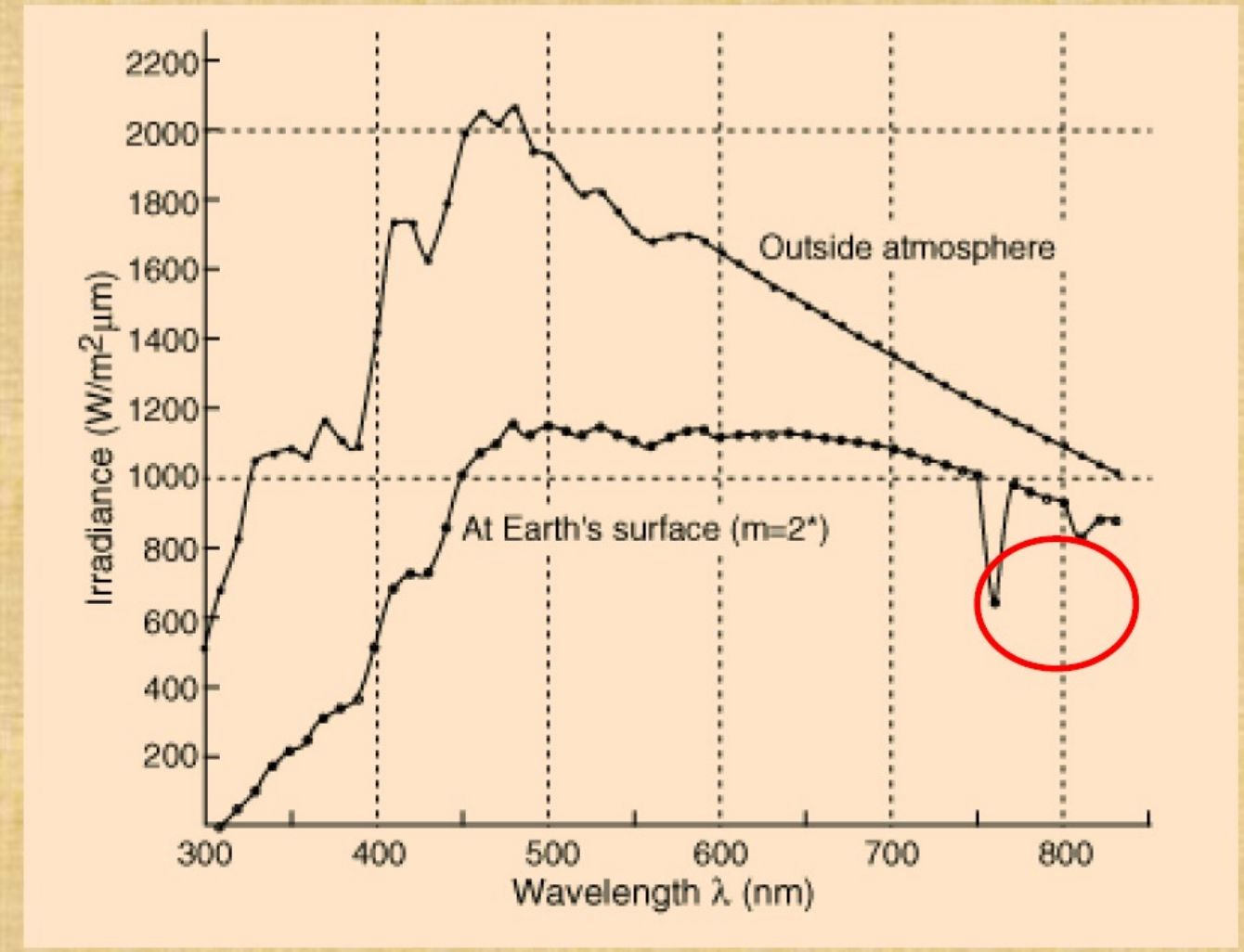
f)the far infrared (FIR): 30 µm to 1

NIR DOMAIN IS IMPORTANT FOR VEGETATION.

SWIR DOMAIN IS IMPORTANT FOR MINERALS

Source/Illumination: Incident Radiation

Sun:

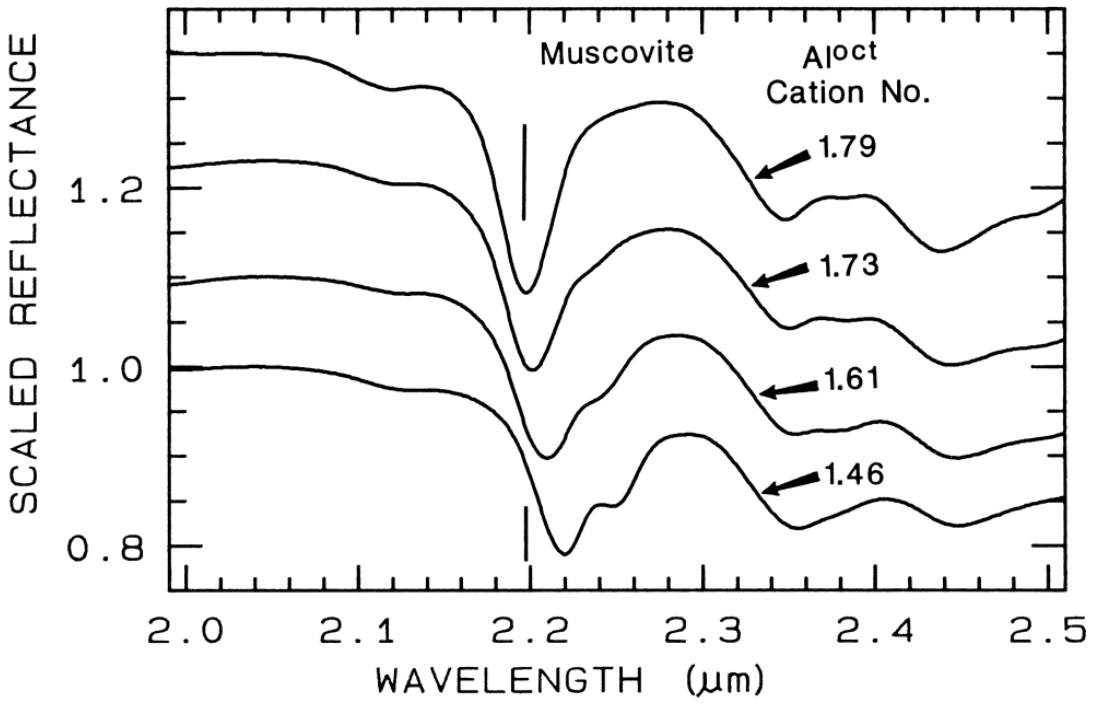


Note: Irradiating light should not have its own features

Argon-Neon Lamp: It may degrade with time

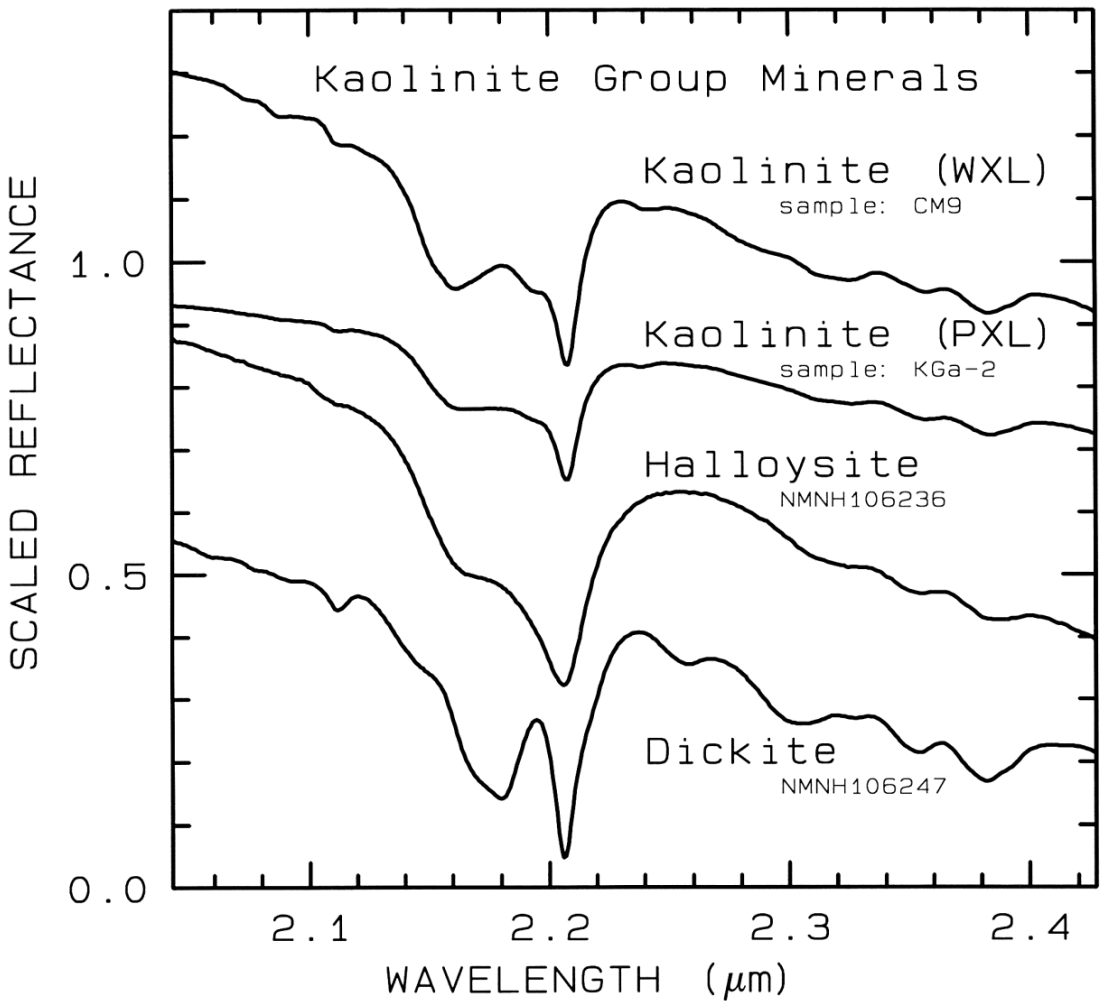
Intrinsic Factor(Target Factor)

Factors influence the spectral signature Changes in Composition



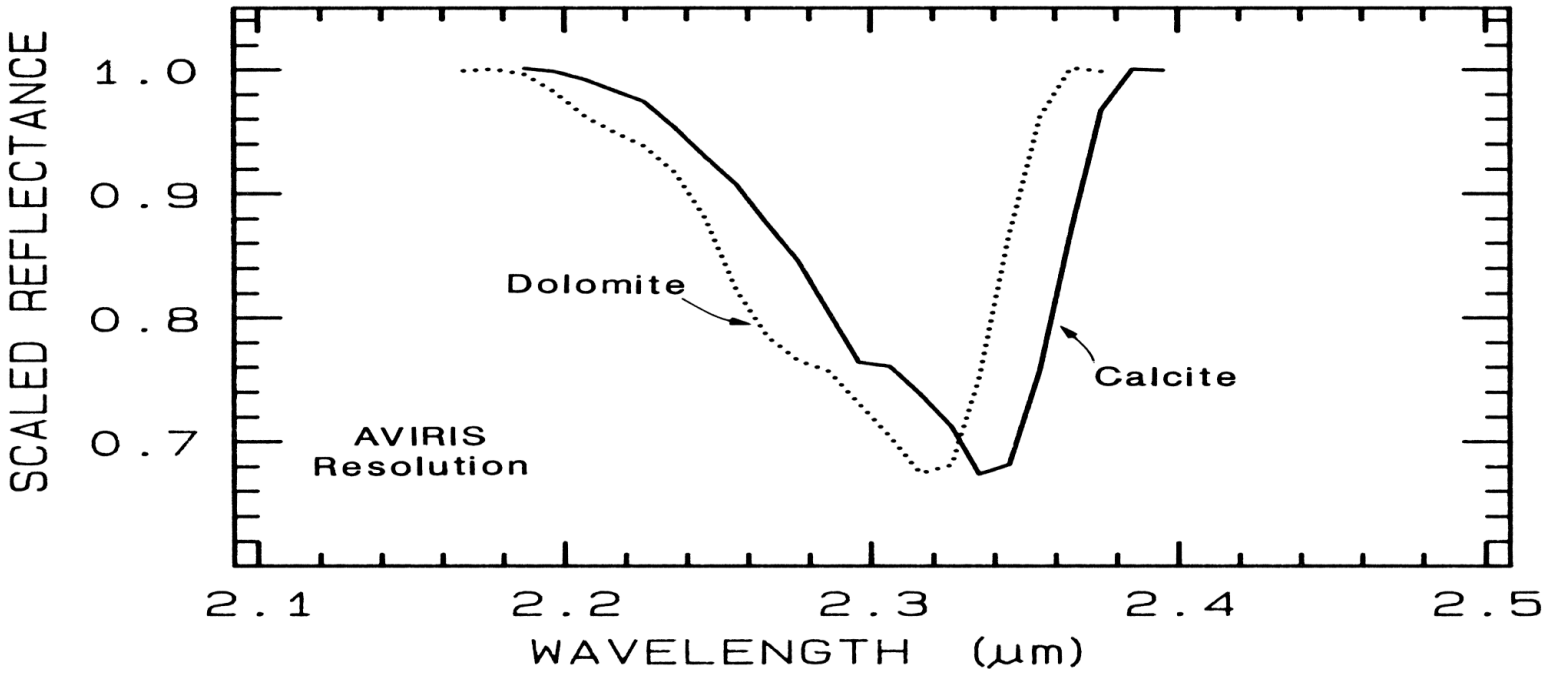
Reflectance spectra of muscovite showing band shifts due to changing aluminum composition

Role of crystallinity



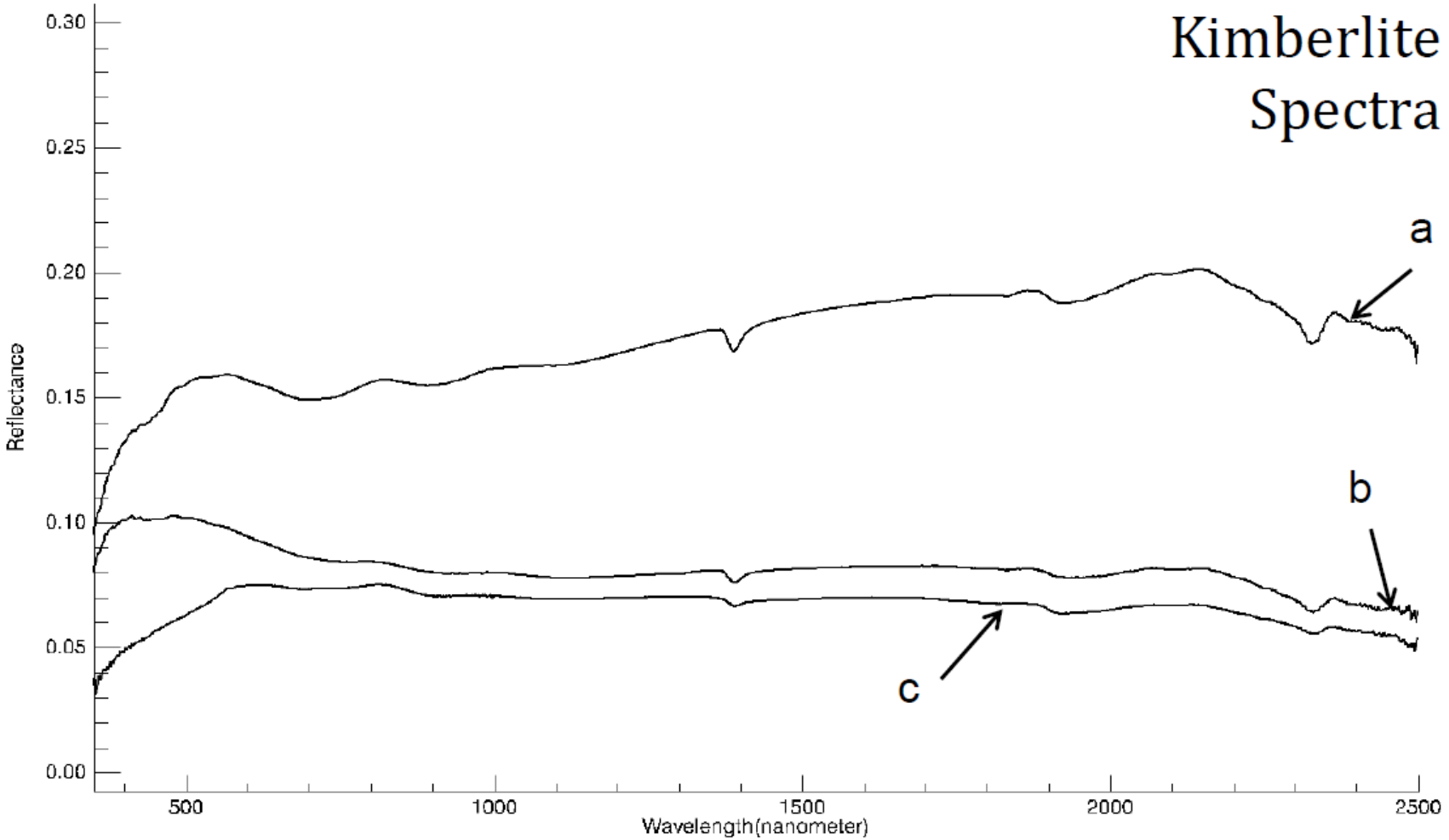
Subtle spectral differences in the kaolinite group minerals near 2.2-µm. KaoliniteCM9 is well crystallized (WXL) while KGa-2 is poorly crystallized (PXL). Spectral bandwidth is 1.9 nm and sampling is 0.95 nm.

Composition plus crystal structure



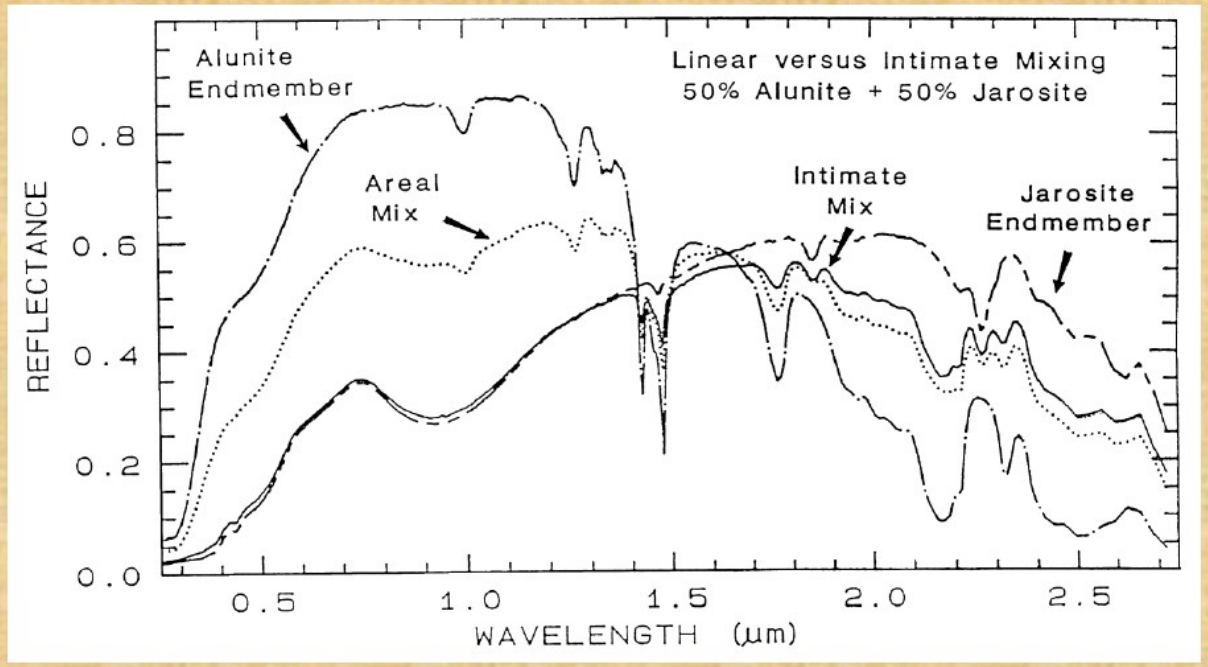
Comparison of calcite and dolomite continuum-removed features. The dolomite absorption occurs at a shorter wavelength than the calcite absorption.

Role of grain size



cba=Reflectance spectra of pulverized sample(<100 micron) of Carbonaceous kimberlite= Reflectance spectra of pulverized sample(60-100 micron) of carbonaceous kimberlite. c= Reflectance spectra of consolidated Carbonaceous kimberlite.

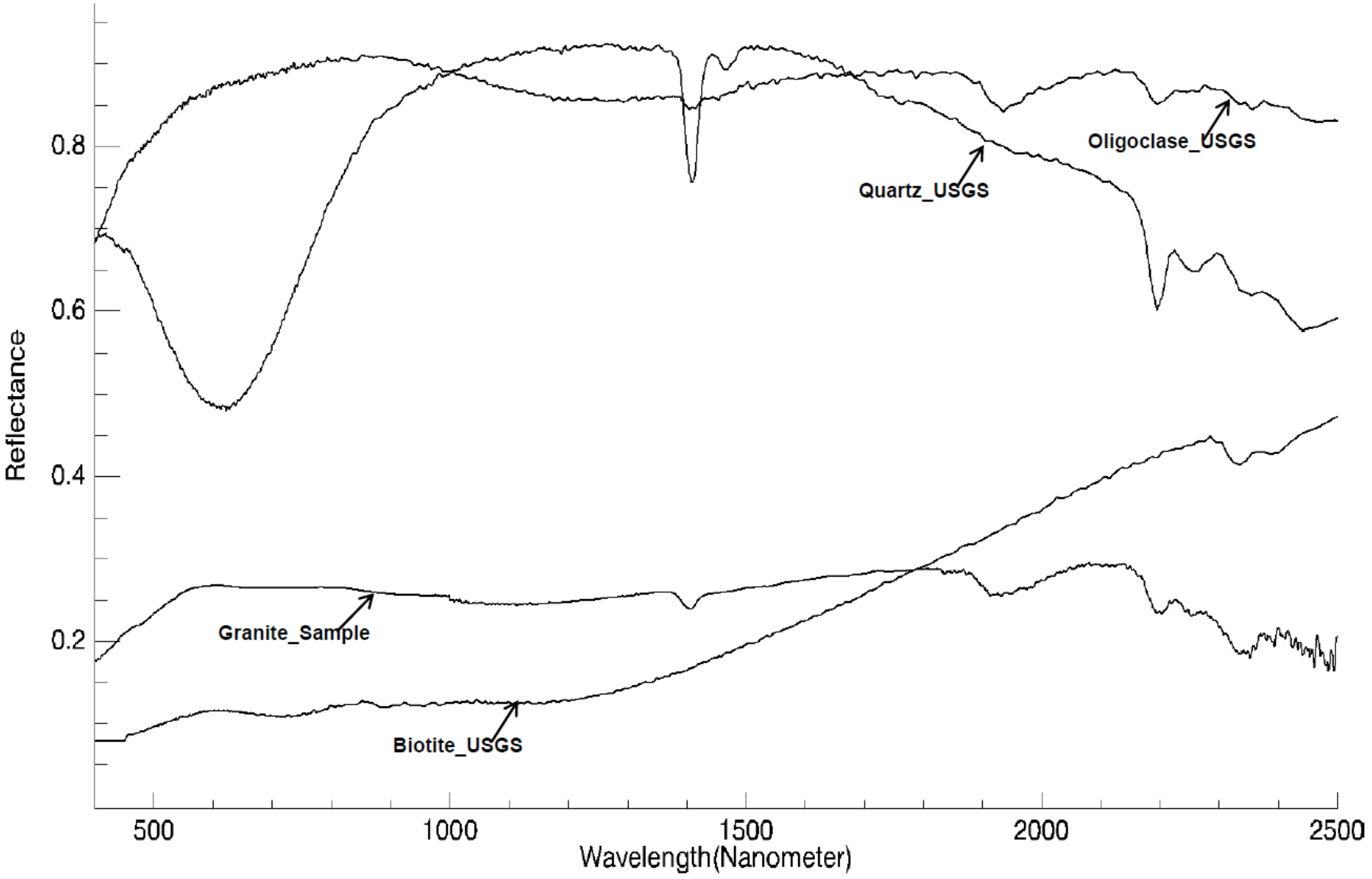
Nature of mixing (Linear and intimate mixtures)



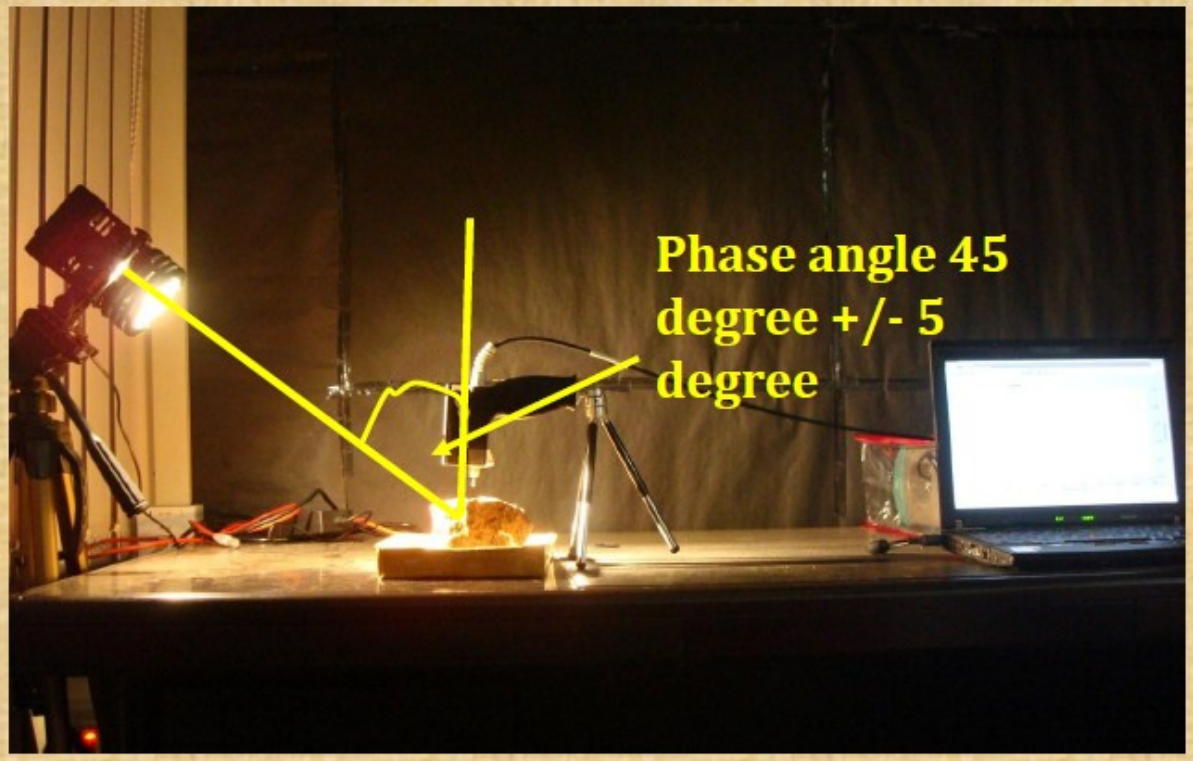
- Two mixture types are shown: intimate and areal. In the intimate mixture, the darker of the two spectral components tends to dominate, and in and areal mixture, the brighter component dominates. The areal mixture(where reflection of one component is not influenced by the other) is a strictly linear in combination.

Relative depth of absorption features drastically change in mixture; wavelength of absorption of spectral feature of a mineral may shift (few nanometers) in mixture

Rock spectra vs Mineral spectra

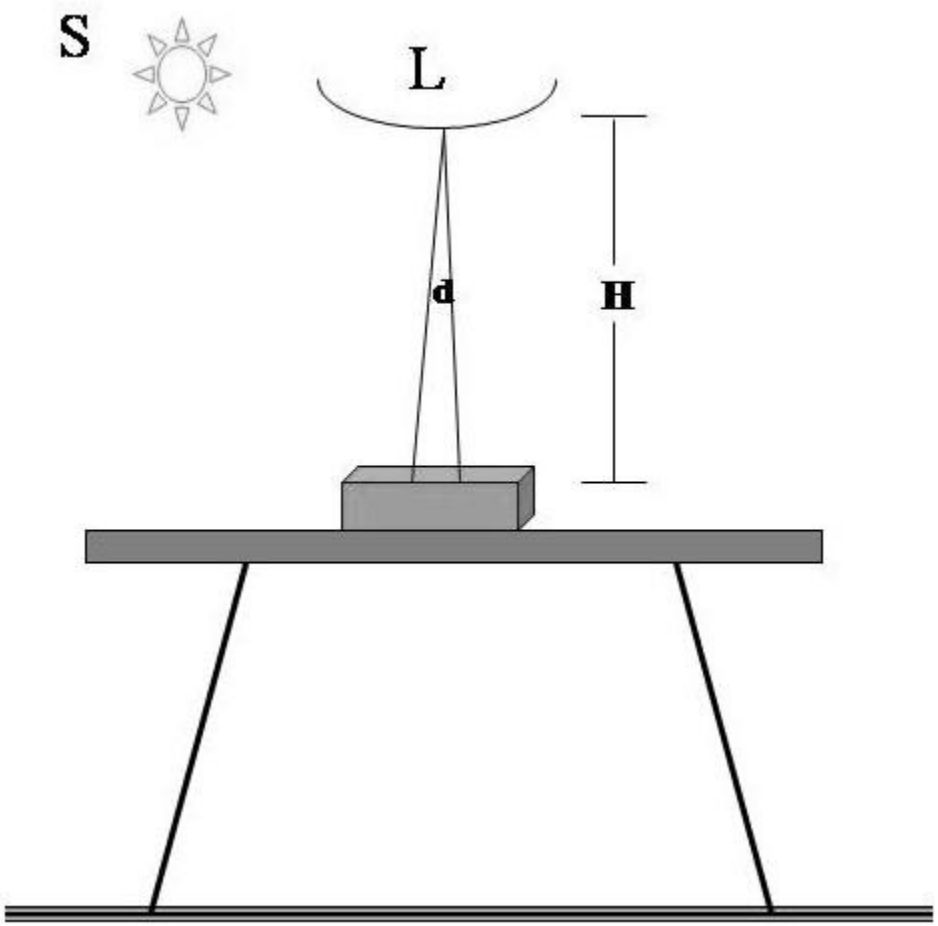


Collection place : Laboratory set up for spectral data measurement



Most data are collected with the sensor mounted vertically over the surface (nadir view).

Laboratory set up



where S is source, L is fiber optic lens where H refers height of the measurement gunfrom the sample top and d indicates the field of view (FOV)of the measurement gun.

Calibration Panel

- Perfectly diffuse reflector.
- Performance of the calibration panel is important
- Maintenance of calibration panel
- Recalibrating the calibration panel.

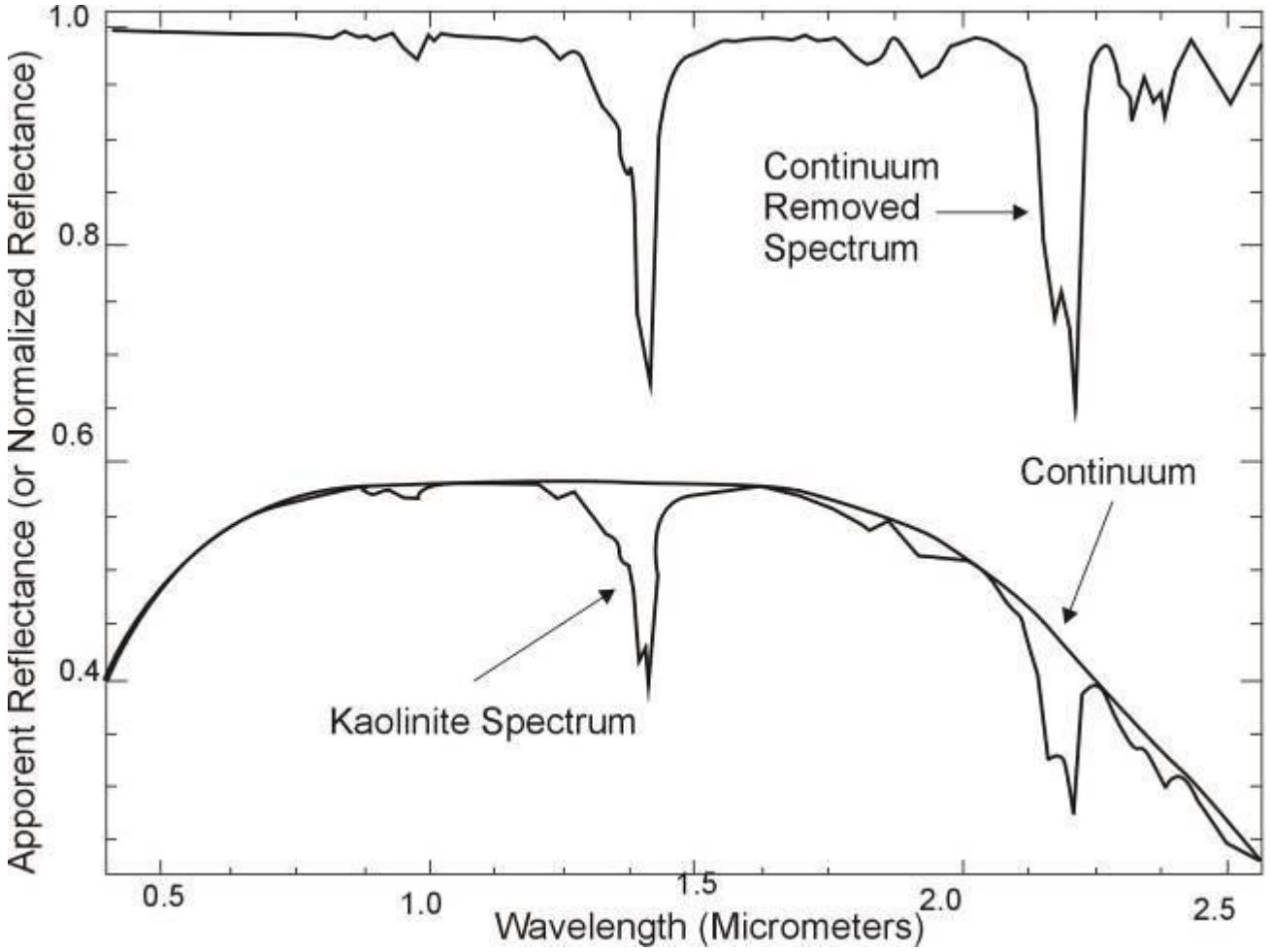
Sample preparation

- Sample(Intact rock sample; size to be specified)
- Grain size of the powdered sample.
- Soil texture should be maintained.
- For few cases; specific grain sized sample is essential.

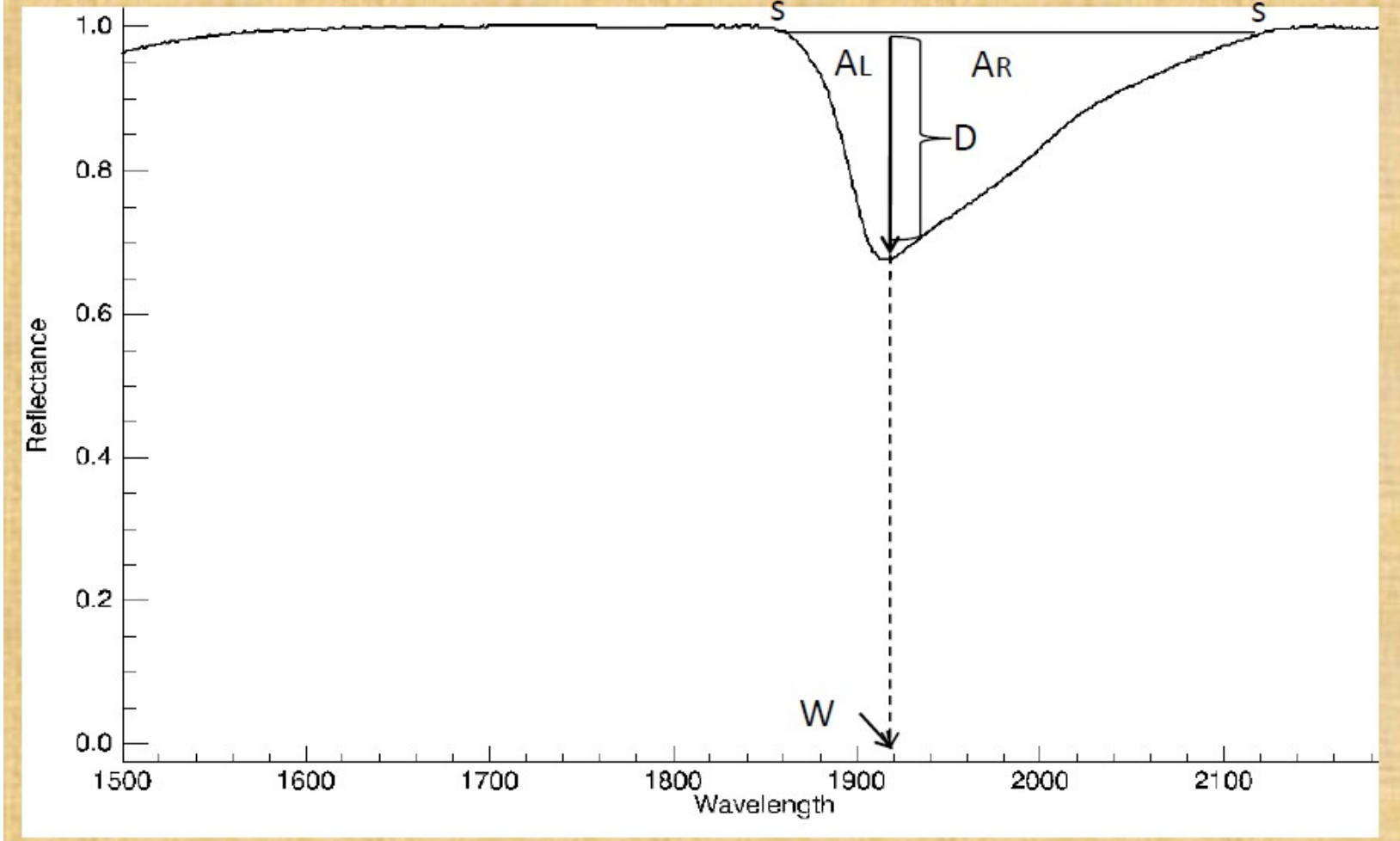
Kimberlite Rock sample

Pulverized Kimberlite Rock sample

Continuum Removal: Continuum is a imaginary line joins highest albedo points in a spectral profile



Properties of Spectra



D= DEPTH

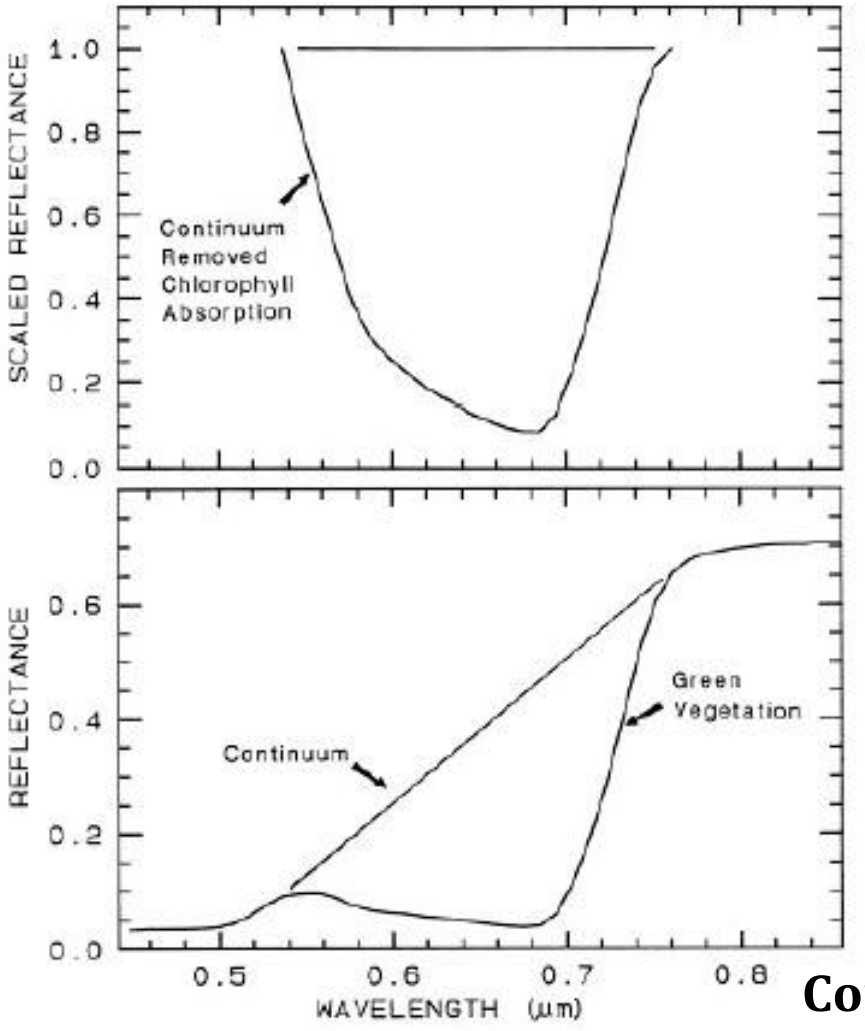
W= WAVELENGTH OF ABS.

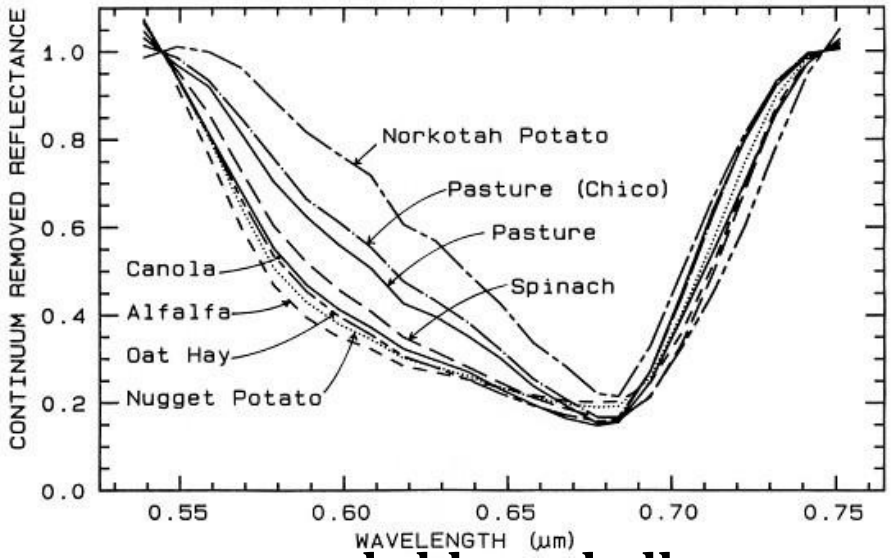
A_L= Area left side of the max. abs.

A_R= Area right side of the max. absorption

measure of asymmetry

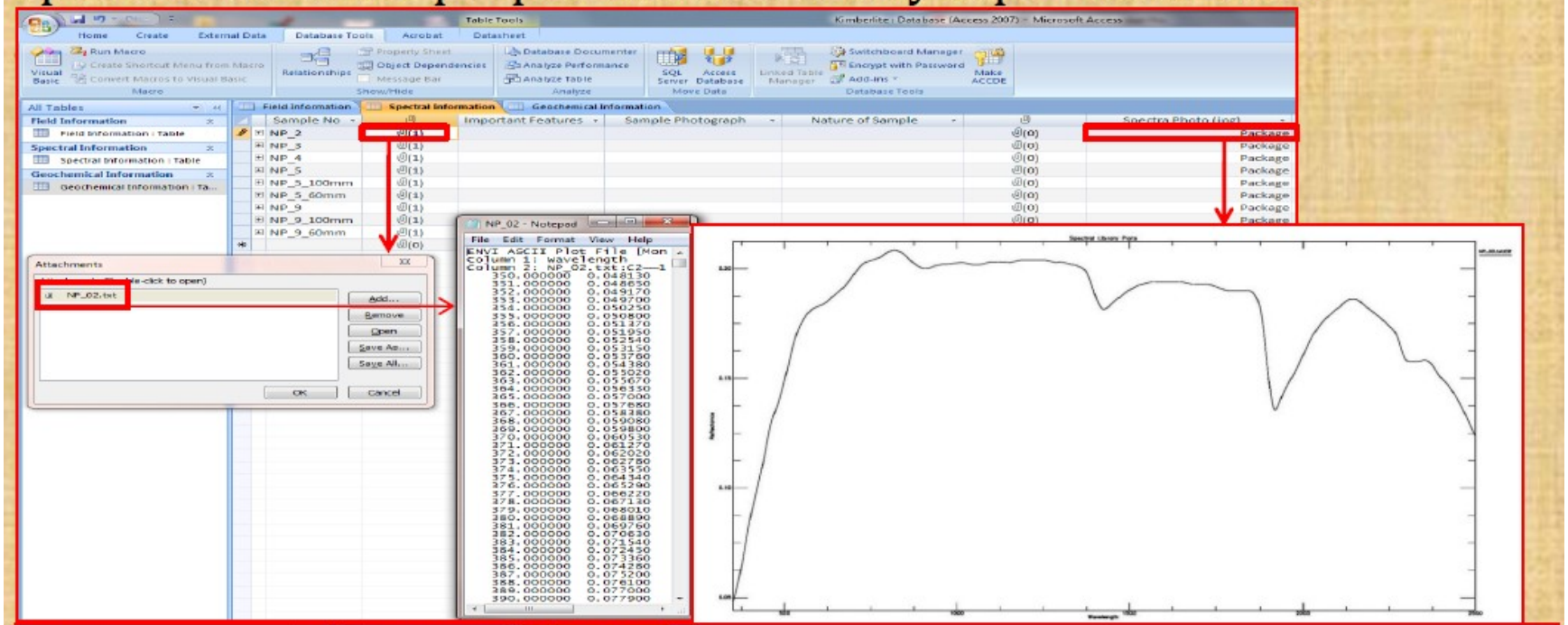
- Continuum removal of vegetation spectra

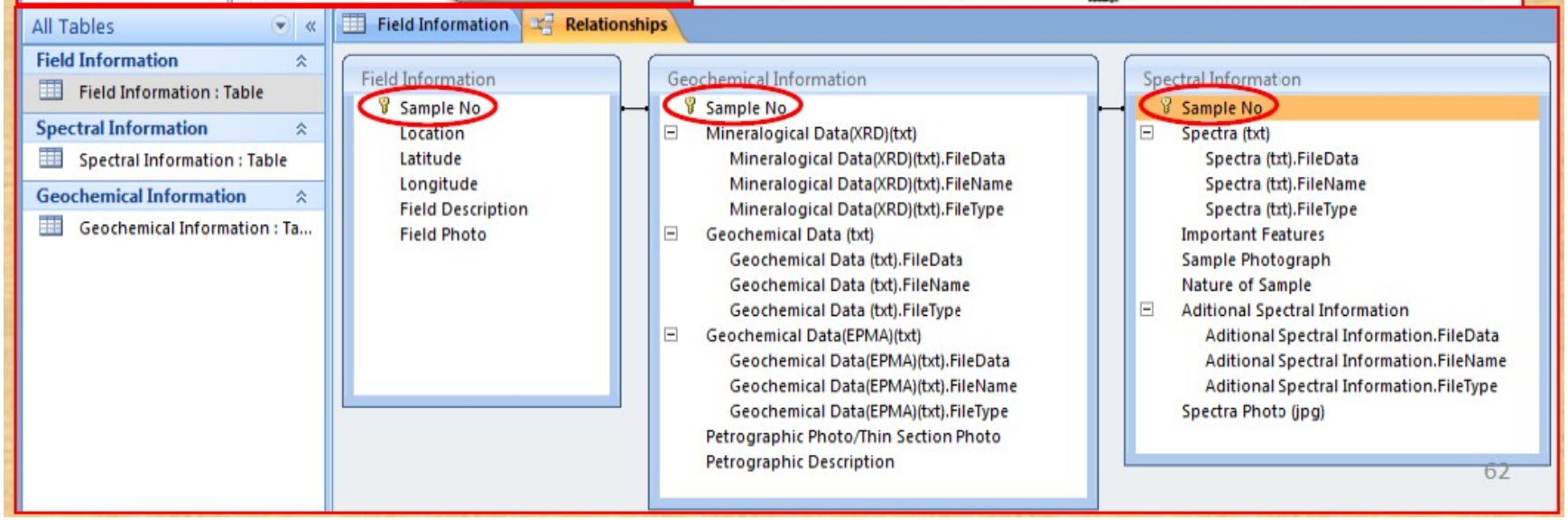




Continuum-removed chlorophyll absorptions for 8 vegetation types showing that the continuum removed features can show subtle spectral differences.

Spectral database preparation for Narayanpet Kimberlite





Noise Estimation and dimensionality reduction in Hyperspectral Data

Data Reduction

- Advances in data collection during past decade Resulting in information overload
- Traditional statistical methods breakdown - Due to Increase in number of Observations & Variables associated with each observation
- Dimension of the data is the number of variables – measured on each observation
- High Dimensional data sets present many challenges
- Major difficulty with high dimensional data
- Not all measured variables are "important" for unraveling phenomena of interest

Commonly used techniques are

Principal Component Analysis – PCA
Minimum Noise Fraction – MNF

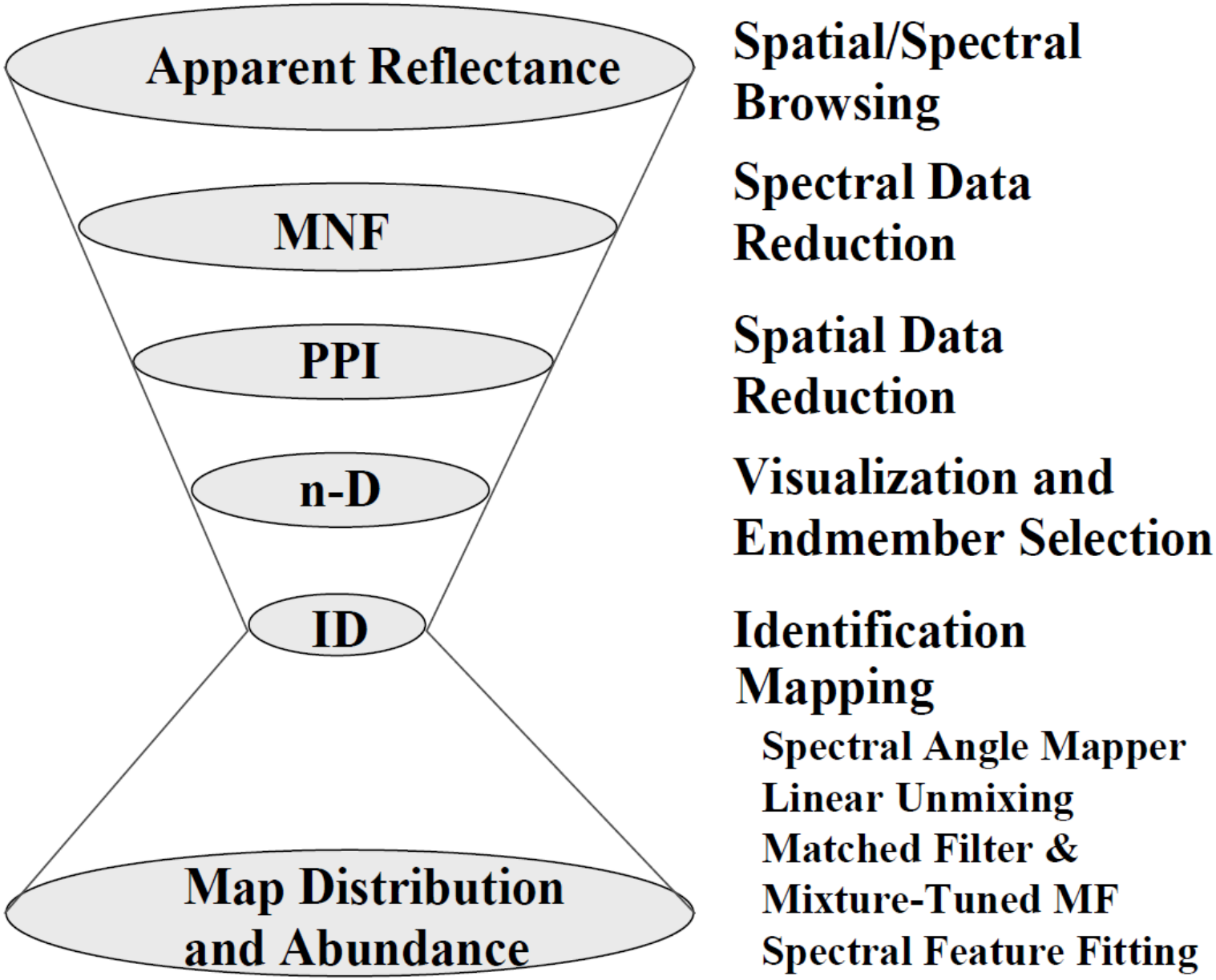


Figure 5. Standardized Processing methods for hyperspectral data analysis.

Principal Components Transform

Different bands of spectral data are often highly correlated - contain similar Information Based on statistical characteristics – data redundancy & correlation between bands can be reduced

Principal Components Analysis - Is a widely used technique for dimensionality reduction & data compression.

PCA Objective is to reduce dimensionality (i.e. the number of bands) in the data, and compress as much of the information in the original bands into fewer bands "NEW" bands that result from this statistical procedure are called components

Process attempts to maximize (statistically) the amount of information (or variance) from the original data into least number of new components

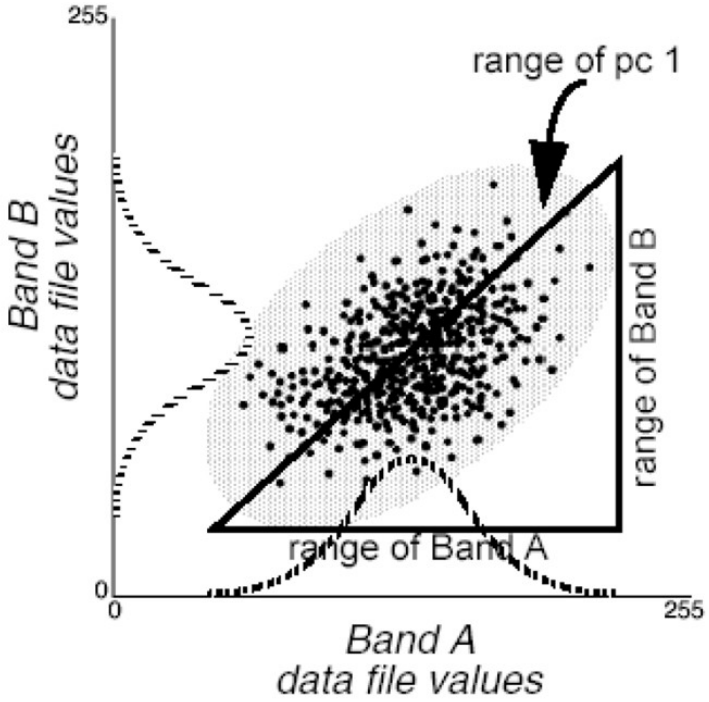
Principal Components Analysis

Uses Eigen values determine the significance of PC

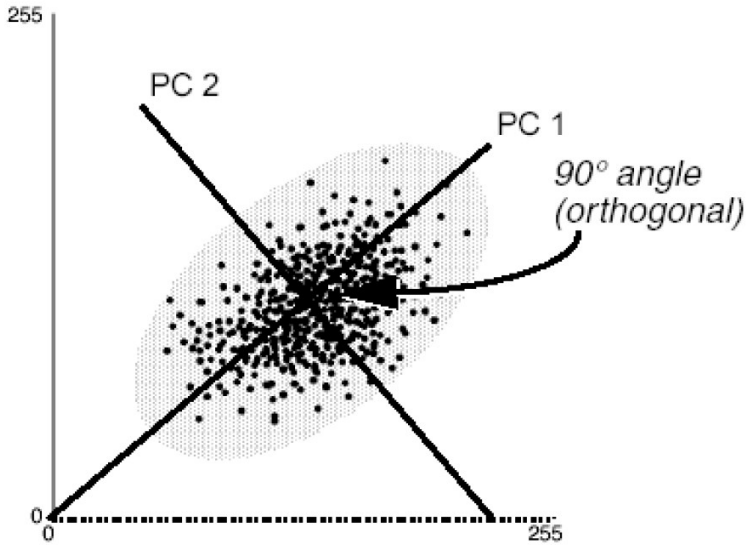
Data Reduction is in accordance with associated eigenvalues

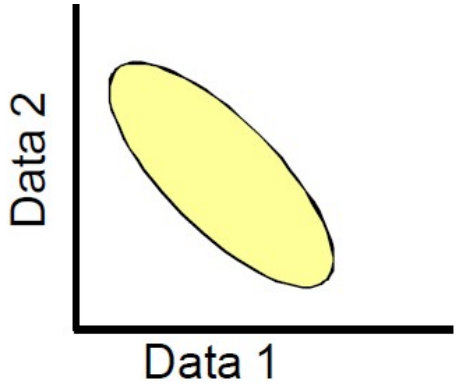
First principal component shows the direction and length of the widest transect of the ellipse, measures the highest variation within the data.

Second principal component is the widest transect of the ellipse that is orthogonal (perpendicular) to the first principal component Second principal component describes the largest amount of variance in the data that is not already described by the first principal component In a two-dimensional analysis the second principal component corresponds to the minor axis of the ellipse

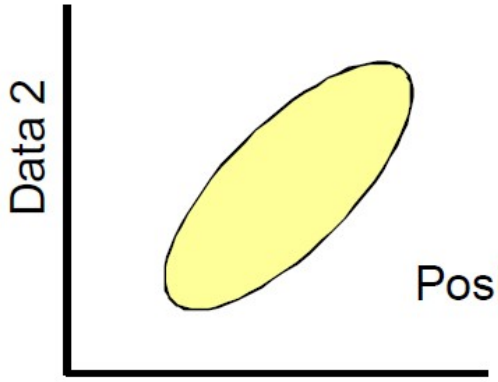


Range of First Principal Component

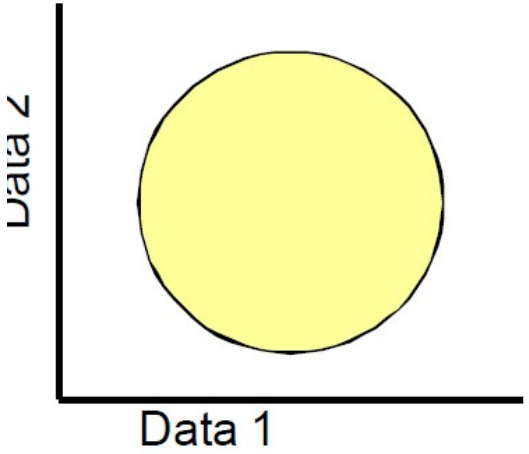




Negative Correlation

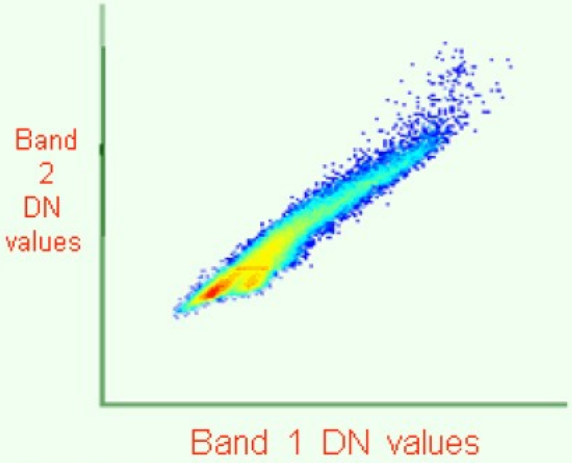


Positive Correlation

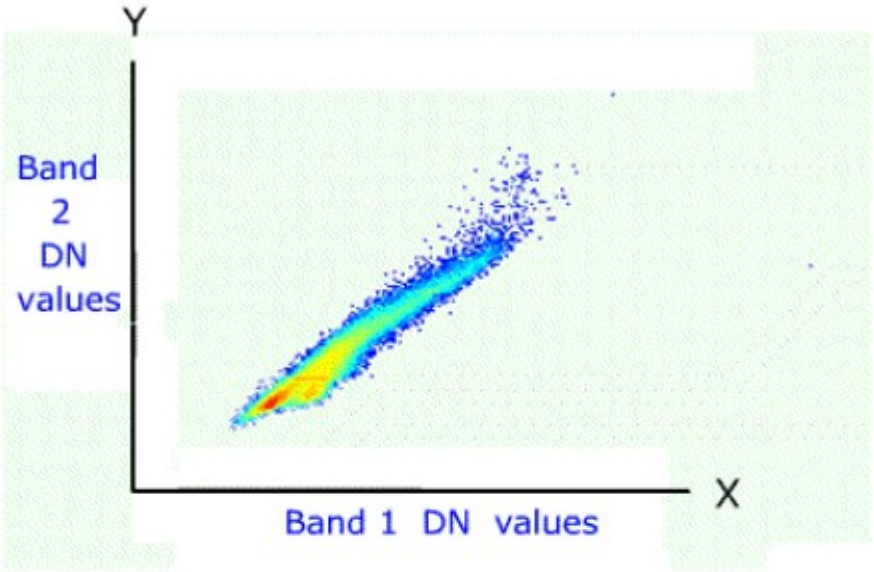


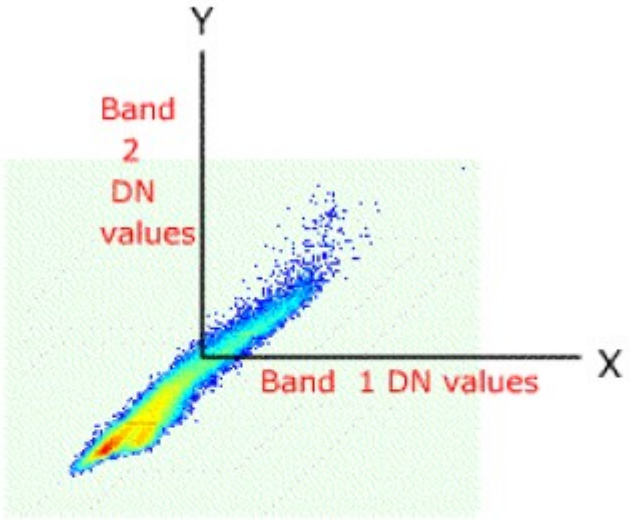
No Correlation

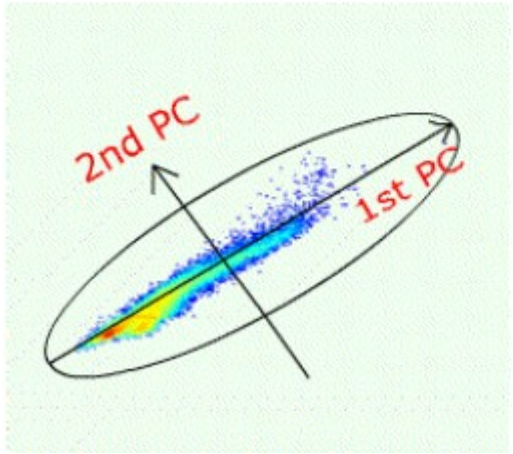
Scattergram of the original image

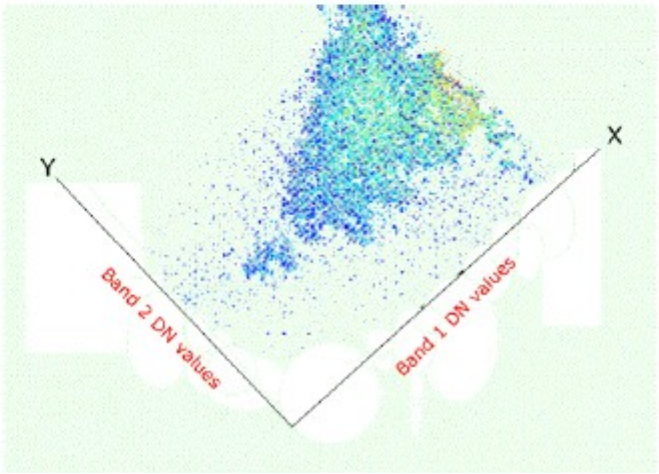


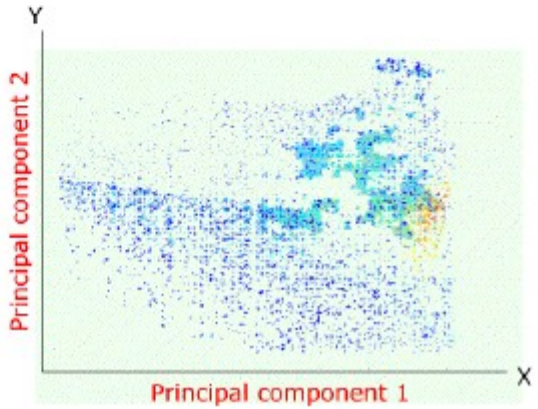
Elliptical shape : highly correlated data


Y
Band
2
DN
values
X
Band 1 DN values


Y
Band
2
DN
values
X
Band 1 DN values


2nd PC
1st PC


Y
X
Band 2 DN values
Band 1 DN values


Y
Principal component 2
X
Principal component 1

In *n* dimensions, there are *n* principal components

Each successive principal component: *Accounts for a decreasing amount of the variation in the data which is not already accounted for by previous principal components*

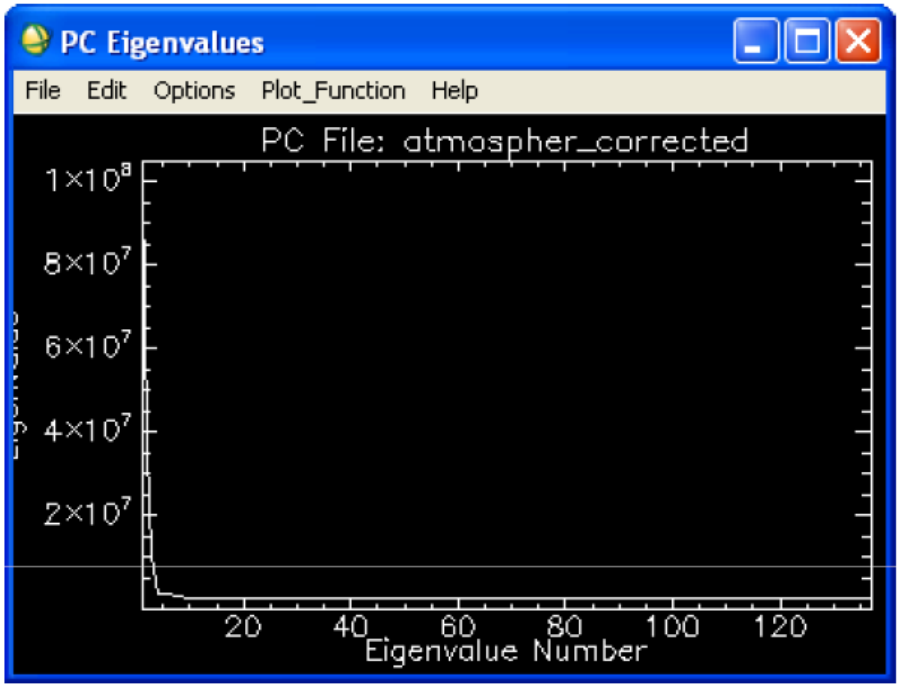
Although there are *n* output bands in a PCA. First few bands account for a high proportion of the variance in the data in some cases, almost 100%.

PCA is useful for compressing data into fewer bands Useful information can be gathered from principal component bands

By seeing this plot we can see that eigen values are high for initial few bands and after eigen value number 6-7 (band 6-7) eigen value is constant.

Eigen values have direct relation with the variance of the data higher the eigen value the variance is more and the information is more.

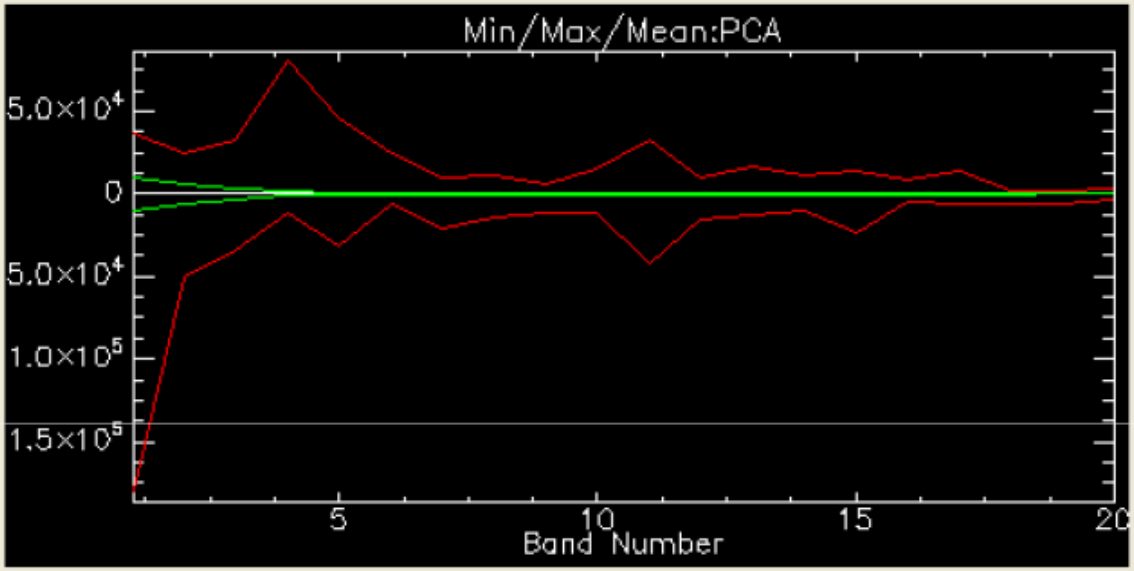
Therefore for further processing only these few bands will be selected. The first band contains the largest percentage of data variance and the second PC band contains the second largets data variance and so on the last bands appear noise as they contain little variance



Statistics Results: PCA

File Options

Select Plot | Clear Plot



Select Stat

Filename: C:\Documents and Settings\Administrator\Desktop\Output\PCA
Dims: Full Scene (800,768 points)

Basic Stats	Min	Max	Mean	Stdev	Num	Eigenvalue
Band 1	-180263.953125	36829.109375	0.000002	10129.544918	1	102607680.255862
Band 2	-50345.183594	24318.552734	0.000002	5991.169248	2	35894108.958115
Band 3	-34717.691406	32464.443359	-0.000000	3203.711874	3	10263769.769036
Band 4	-11300.982422	79923.171875	-0.000000	1161.727255	4	1349610.214844
Band 5	-31863.417969	45633.812500	0.000000	1101.156846	5	1212546.399726
Band 6	-5856.978516	24676.527344	0.000000	1028.521395	6	1057856.259518
Band 7	-20937.958984	9371.420898	0.000000	811.807241	7	659030.996098
Band 8	-14590.811523	10512.766602	-0.000000	666.157835	8	443766.261620
Band 9	-11698.884766	5119.298340	0.000000	590.652464	9	348870.333026

PCA1

Red – 750.38 nm
Green – 655.84 nm
Blue – 547.20 nm

PCA2

PCA45

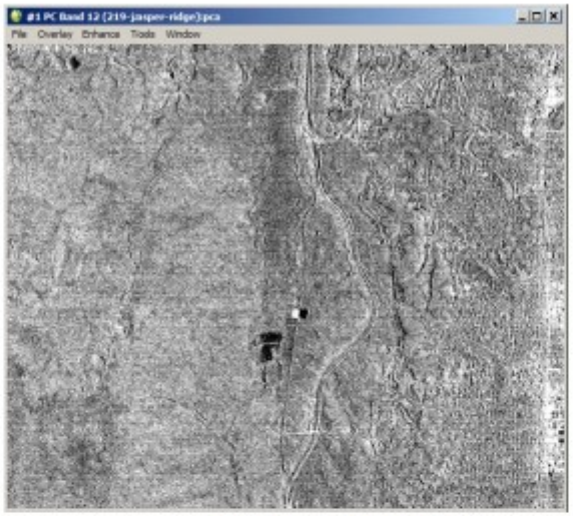
Issues of PCA

PCA maximizes total image variance with out making distinction between Noise & Information

PCA images are ordered by data variance. If bands have differing amounts of noise ?

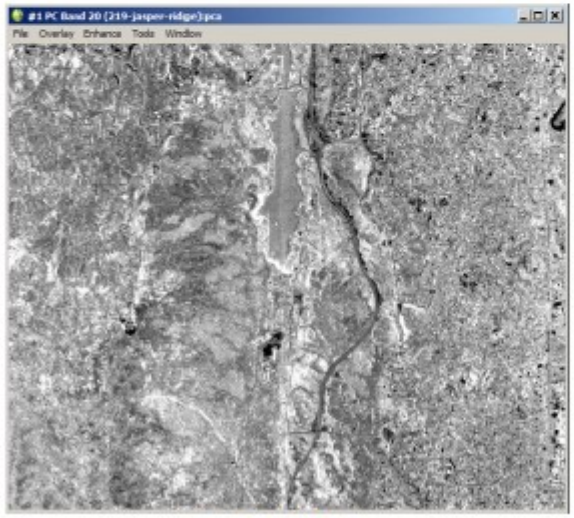
Bands in a hyperspectral image have differing amounts of noise Principal components may not show usual trend of steadily increasing noise with increasing component number

PCA11



PCA12 - Noisy

PCA13



PCA20

PCA21 - Noisy

PCA22

Distinction between information & noise can be made

- Some sensor systems simultaneously acquire dark images.
- Dark Current images represent electronic noise present in the data
- These dark images can be used as input for noise estimation

Absence of dark images -If we assume that

Signal at any point in the image is strongly correlated with the signal at neighboring pixels while the noise shows only weak spatial correlation

Near neighbor differences can be averaged to derive noise value

Minimum Noise Fraction Transform
Shift Difference method

It is assumed that each pixel contains both signal and noise, and that adjacent pixels contain the same signal but different noise

"shift difference" is performed on the data by differencing adjacent pixels and averaging the results to obtain the "noise" value to assign to the pixel being processed

Best noise estimate is gathered using the shift-difference statistics from a homogeneous area rather than from the whole image

Minimum Noise Fraction transform (MNF) orders output components by decreasing signal to noise ratio

MNF procedure first estimates the noise in each image band using the spatial variations in brightness values

Then applies two successive principal component transforms

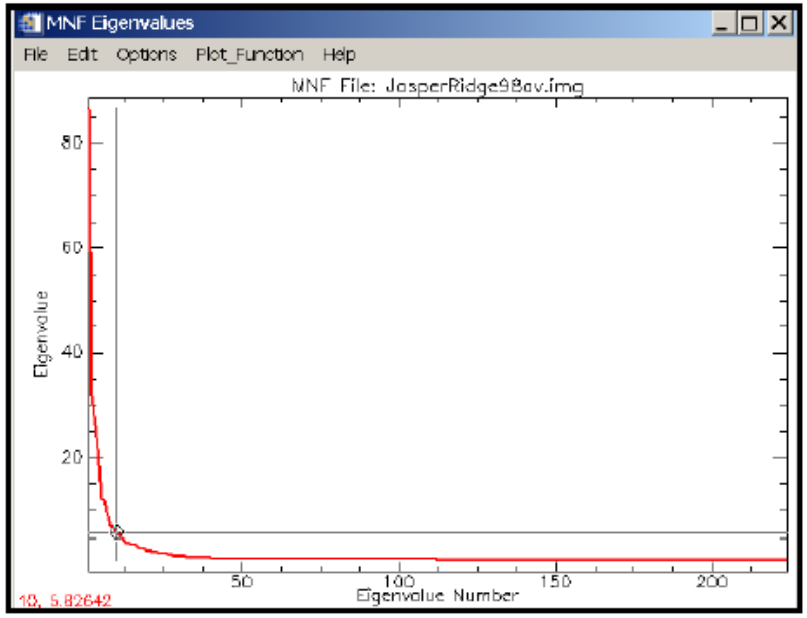
First uses the noise estimates to transform the dataset to a coordinate system in which the noise is uncorrelated and is equal in each component

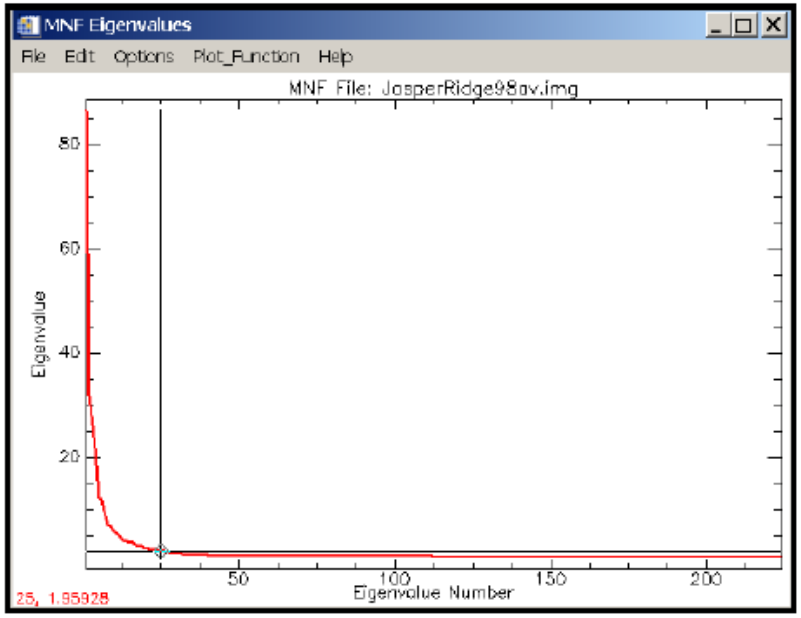
Then a standard principal components transform is applied to the noise-adjusted data, with output components ordered by decreasing variance

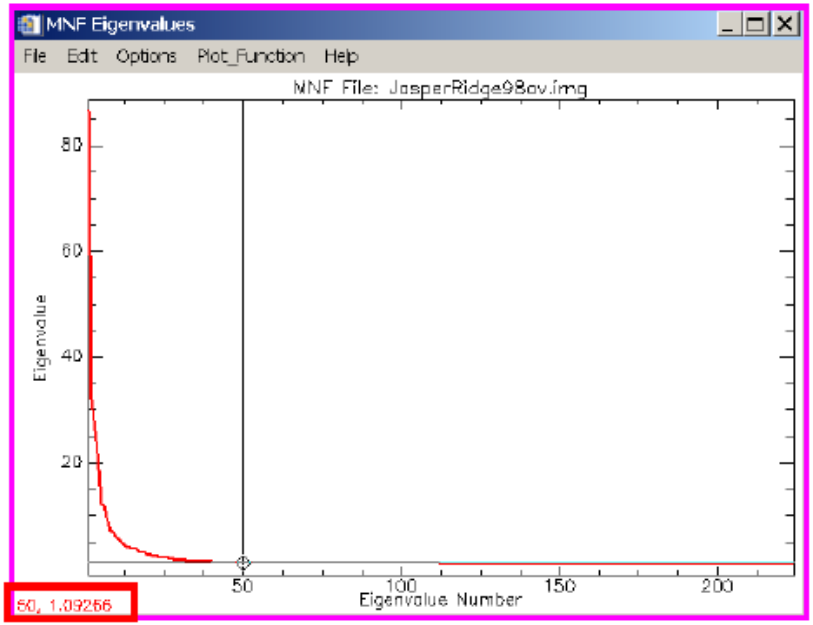
Procedure produces a component set in which noise levels increase uniformly with increasing component number

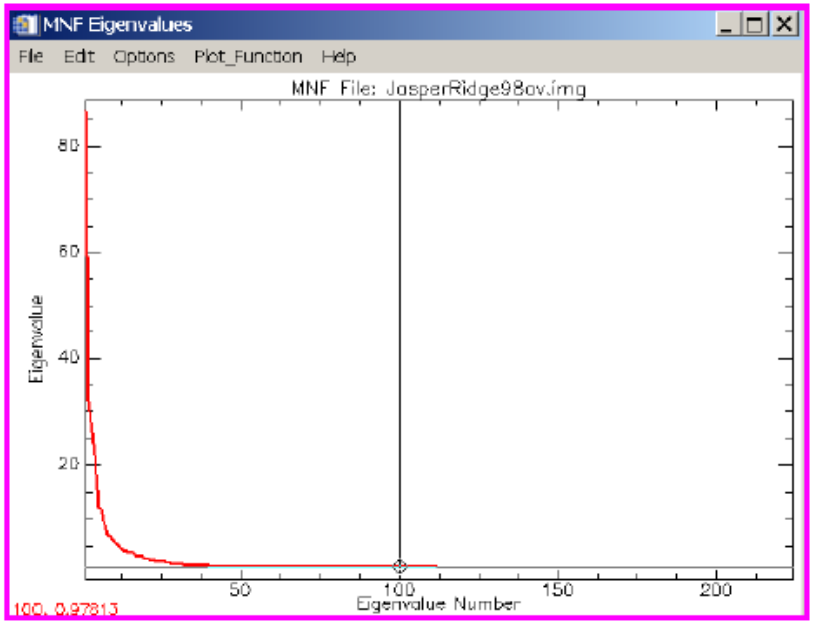
Low-order components should contain most of the image information and little image noise

MNF Eigen Value Plot



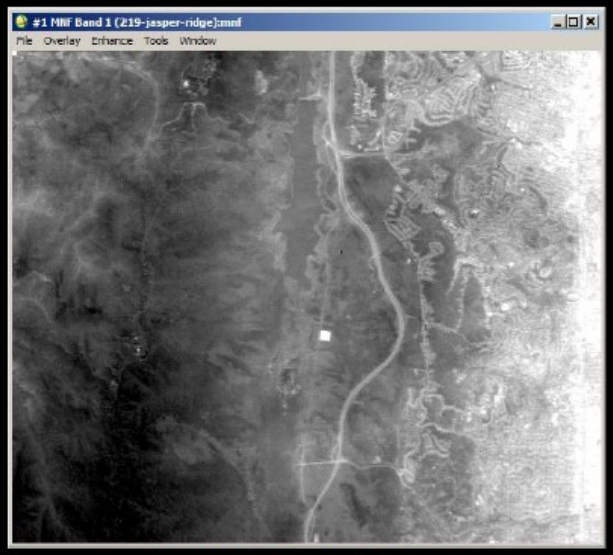






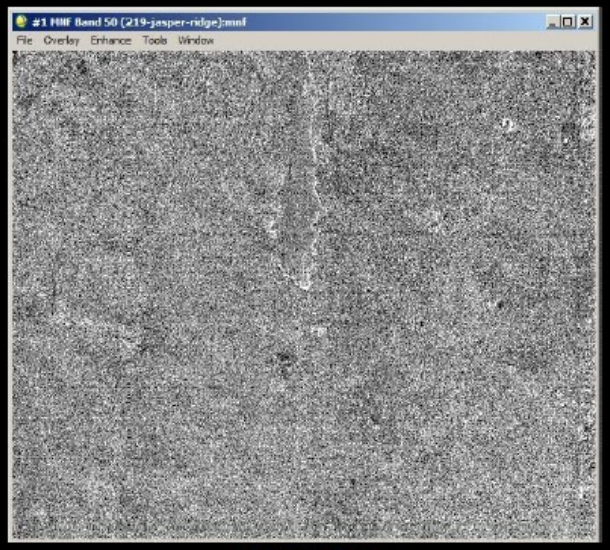
INFORMATION PRESENT IN 224 AVIRIS BANDS CAN BE COMPREESED TO 50 BANDS

Noise - Full image



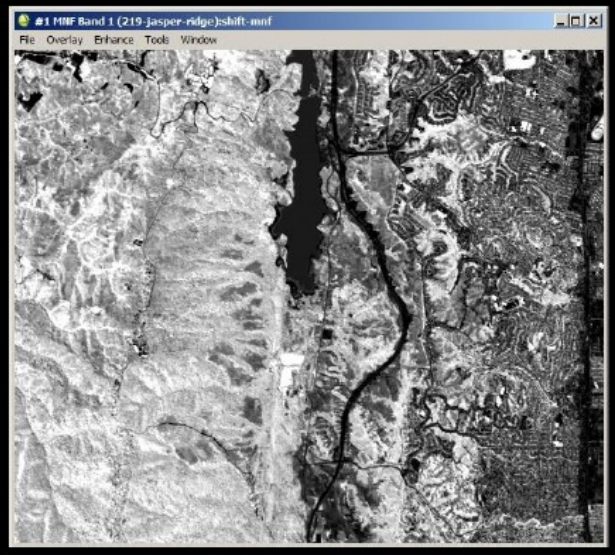
MNF1 - HAZY

MNF2



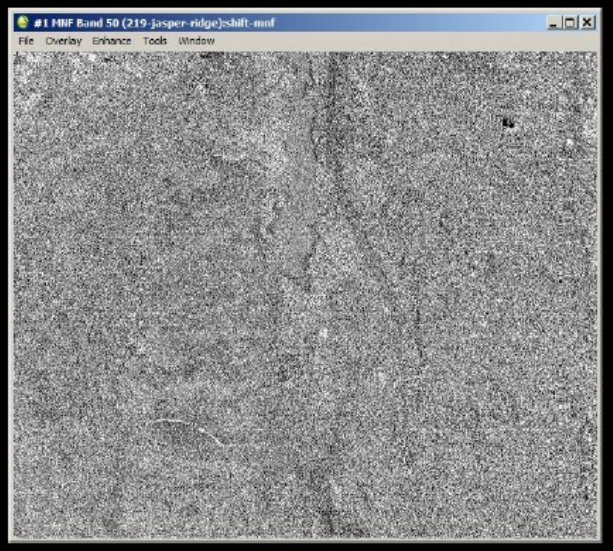
MNF50

Noise –water body



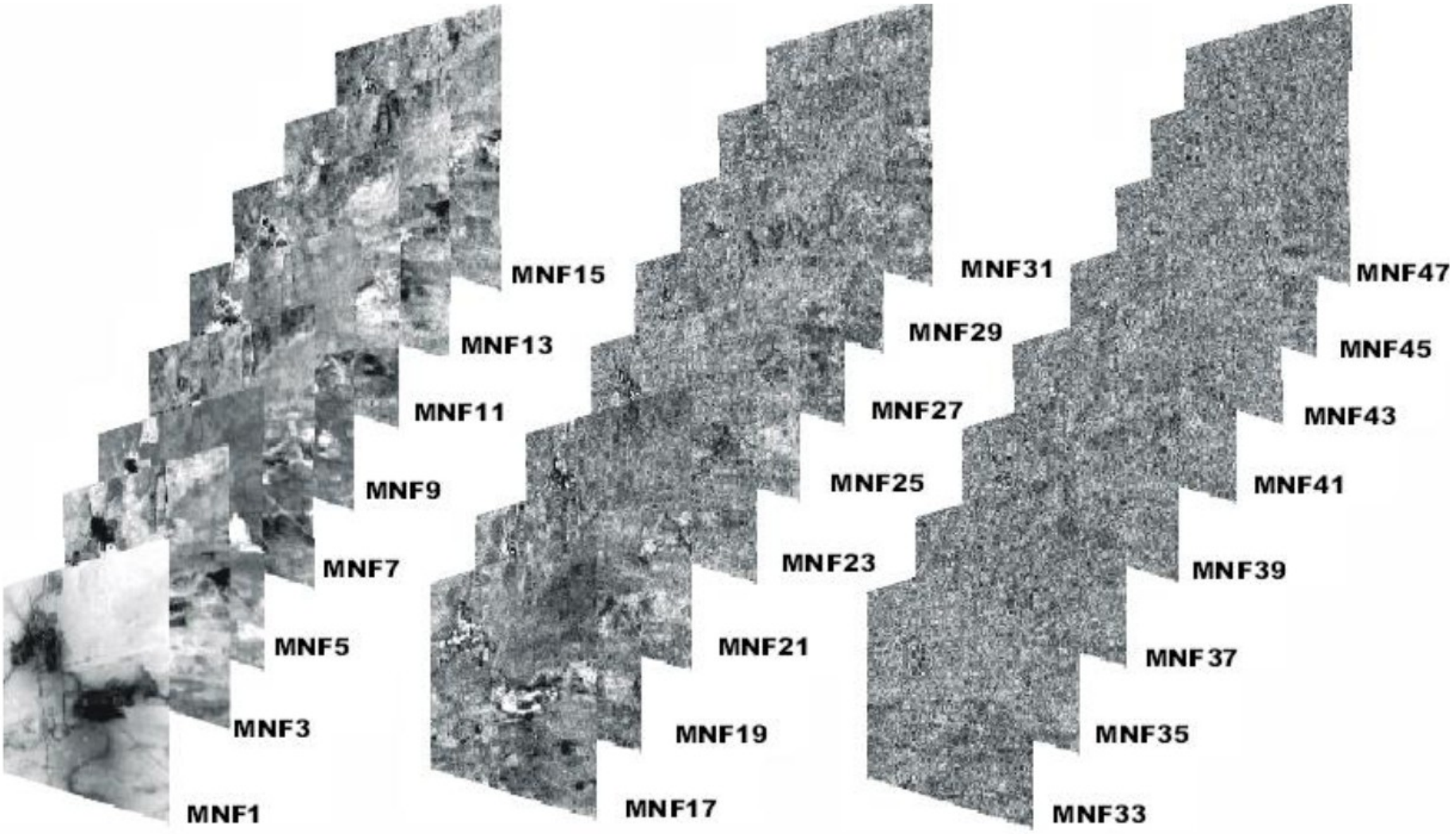
MNF1 - CLEAN

MNF2

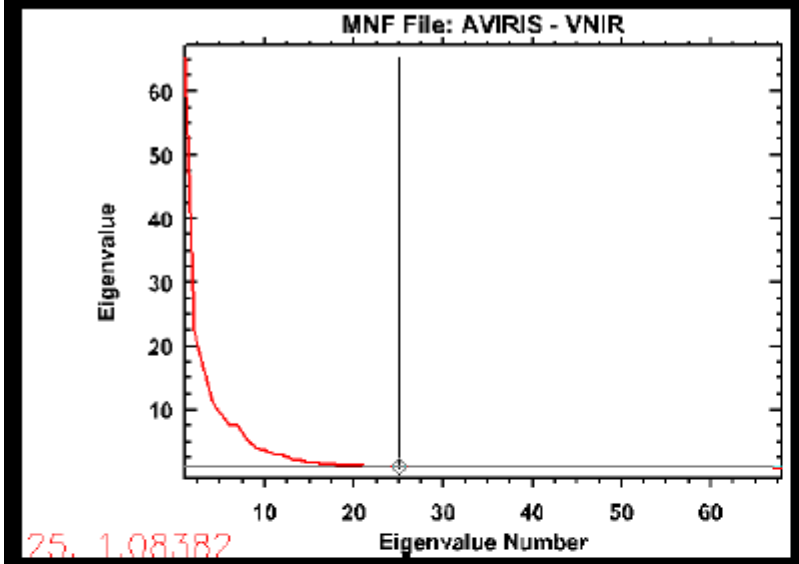


MNF50

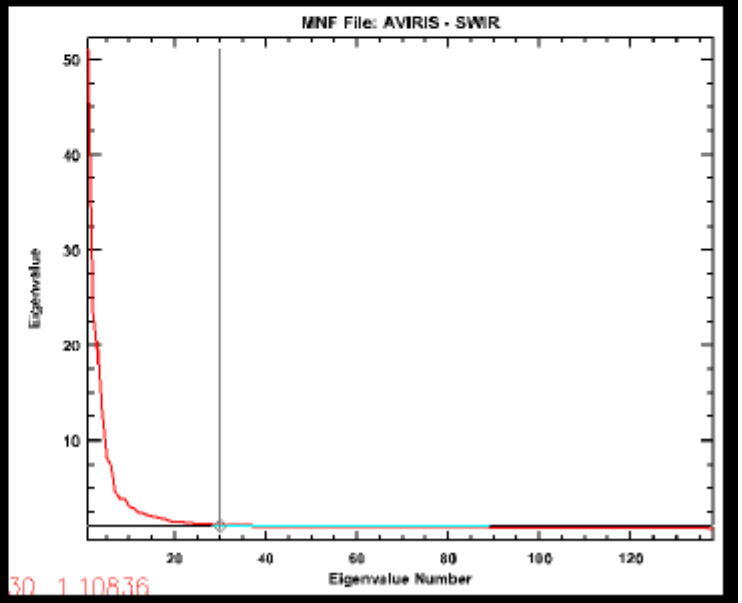
Degradation of the signal all along the MNF components



MNF IS PERFORMED SEGREGATING DATA INTO VNIR & SWIR SEGEMENTS



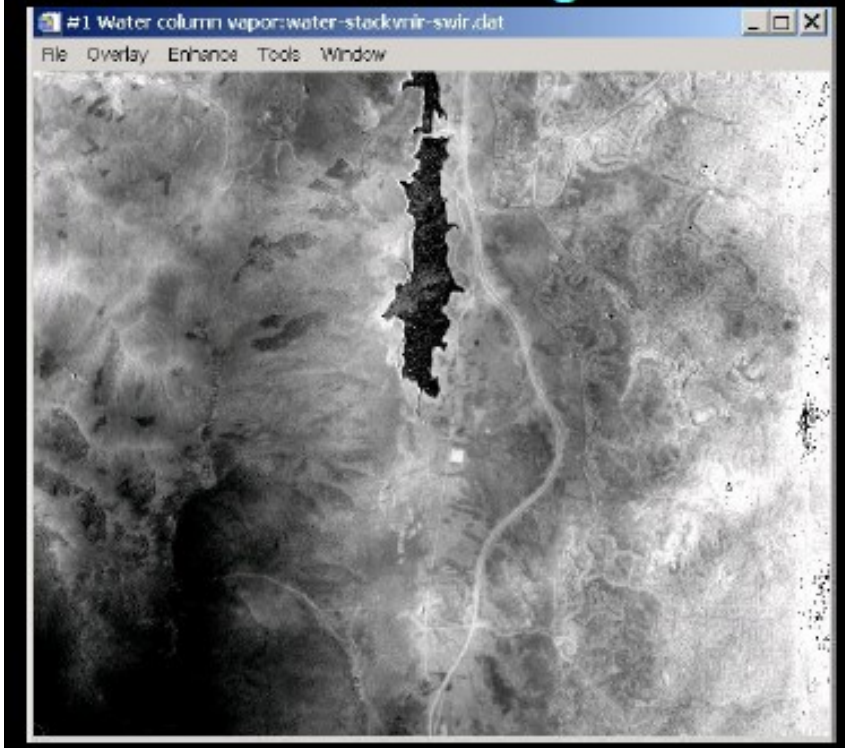
Inverse - Using first 25 MNF bands



Inverse - Using first 30 MNF bands

FLAASH - WATER VAPOUR IMAGE

Noise Reduced Using MNF



LARGELY NOISY FREE OVER WATER FEATURE

With out noise Reduction

NOISY OVER WATER FEATURE

MNF is useful in determining inherent dimensionality of image data by segregating noise and reduce computational requirements for subsequent processing

Pixel Purity Index

The set of low-order MNF components provides a "distilled" version of the hyperspectral image that can be used to rapidly identify relatively "pure" image spectra for use as spectral endmembers in the further processes.

The Pixel Purity Index (PPI) operation is the first step in identifying these endmember spectra.

Pixel Purity Index

The "Pixel-Purity-Index" (PPI) is a means of finding the most "spectrally pure," or extreme, pixels in multispectral and hyperspectral images. See Boardman *et al* . (1995).

PPI calculates a spectral purity score for each n-dimensional pixel in the original data by generating random unit vectors (called skewers), so that all pixel vectors are projected on to the skewers and the ones falling at the extremes of each skewer are counted. After many repeated projections to different skewers, those pixels that count above a certain cut-off threshold are declared "pure"

A Pixel Purity Index (PPI) image is created in which the DN of each pixel corresponds to the number of times that pixel was recorded as extreme

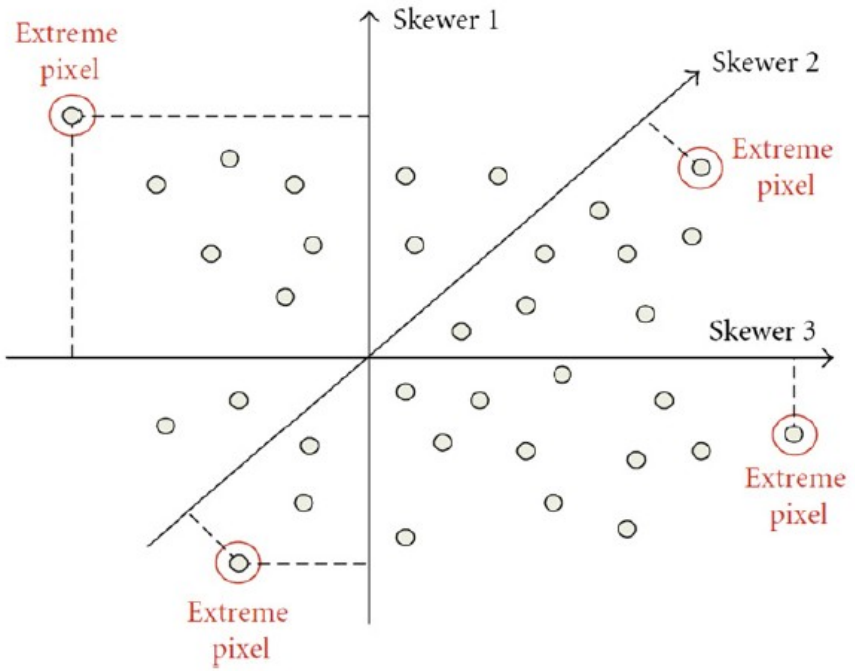
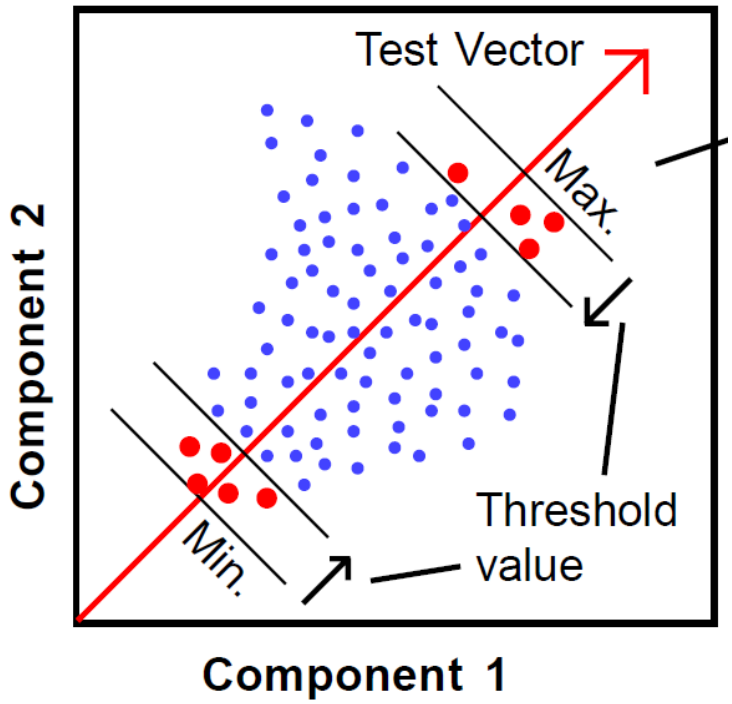
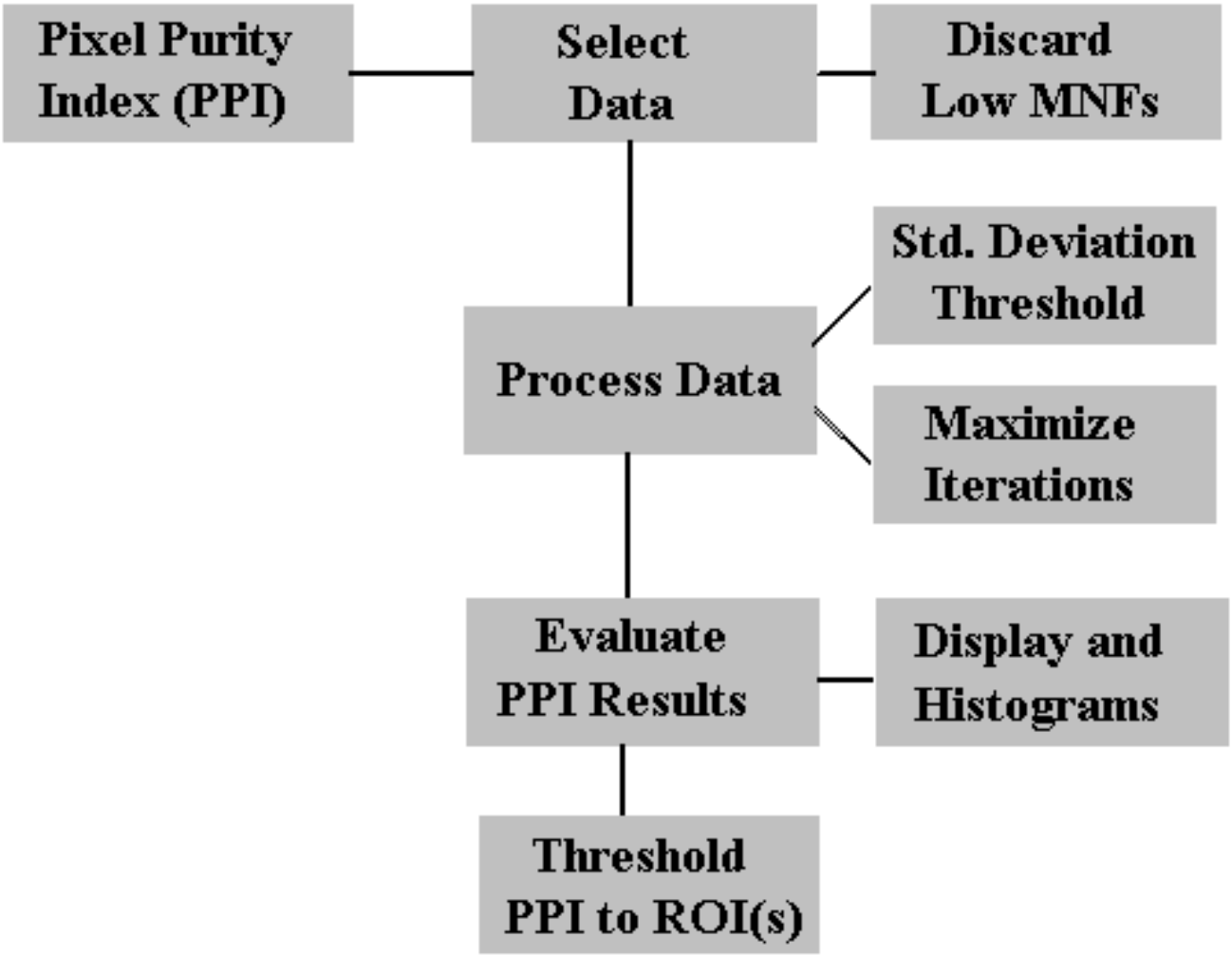


Fig. 3. Toy example illustrating the PPI endmember extraction algorithm in a two-dimensional space.



A two-dimensional illustration of how the Pixel Purity Index identifies potential extreme image spectra (large red dots).



Endmembers represent pure pixels supposedly representing one feature type only and these can be collected from image itself

Using PPI images in a n-dimensional visualiser for endmembers collection

Spectra can be thought of as points in an n-dimensional scatterplots, where n is the number of bands.

The coordinates of the points in n-space consist of “n” values that are simply the spectral radiance or reflectance values in each band for a given pixel.

The distribution of these points in n-space can be used to estimate the number of spectral endmembers and their pure spectral signatures.

n-Dimensional Visualizer

To assess the results of the PPI operation we will use the n-Dimensional Visualizer tool.

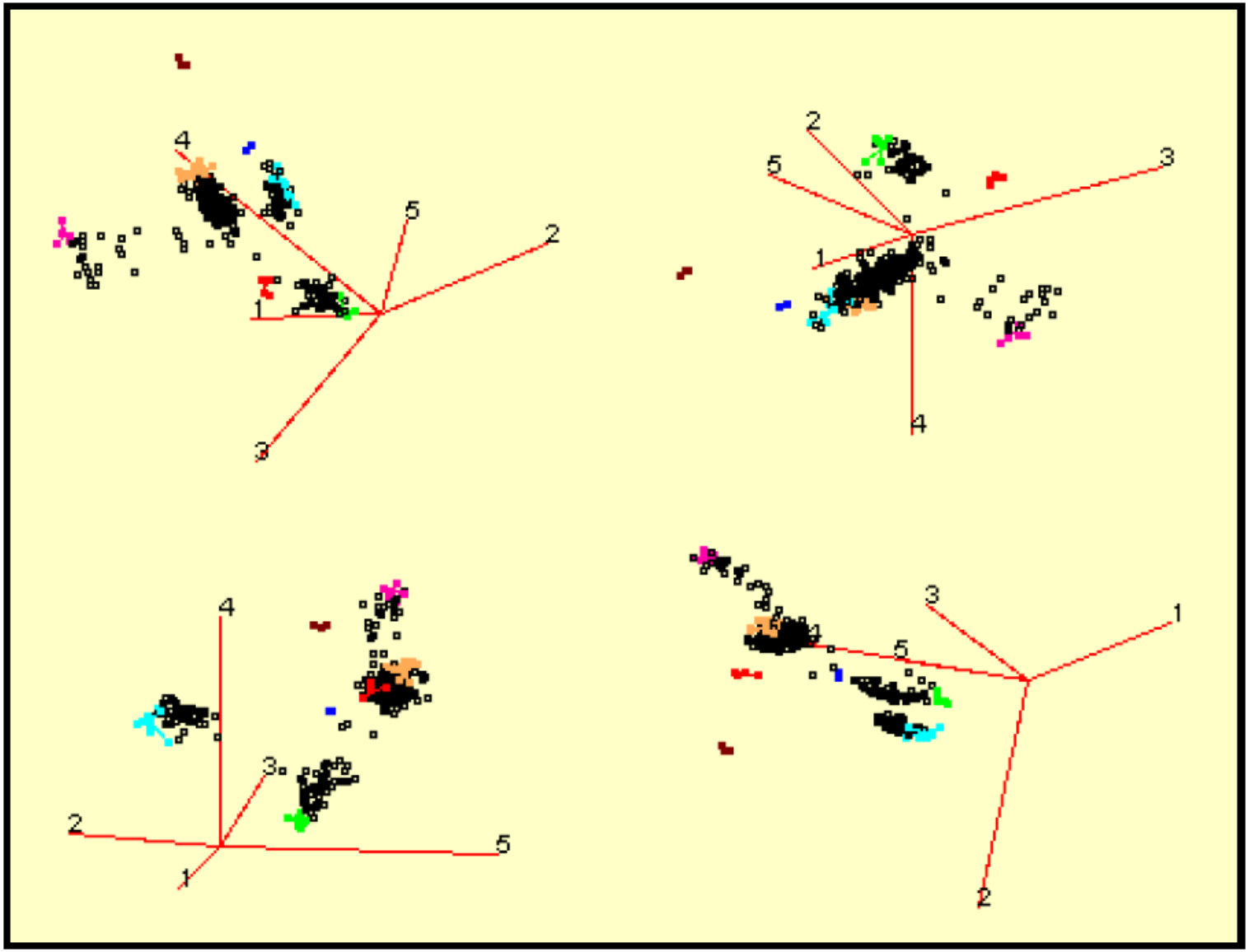
This tool allows you to create and view an n-dimensional scatterplot of spectra for an area in the hyperspectral image or MNF component set. You can view the scatterplot from different viewpoints and rotate the plot manually or automatically in real time.

You designate the selected area by drawing a polygon in the Hyperspectral Image window. You can use this tool to investigate the spectral properties of different materials in the image and to search for image cells with extreme spectral values that might represent pure endmembers

Using PPI images in a n-dimensional visualiser for endmembers collection

The n-Dimensional visualizer provides an opportunity for interactive selection of the endmembers in n-space. The n-D visualizer is used in conjunction with the Minimum Noise Fraction Transform (MNF) and Pixel Purity index (PPI) tools to locate, identify and cluster the purest pixels and most extreme spectral responses in a data set.

The n-Dimensional visulizer allows for interactive rotation of data in n-D space, selection of groups of pixels into different classes (Boardman, 1993; Boardman and Kruse, 1994). Here in this study this procedure was followed to isolate different group of pixels representing different endmembers. The selected classes were exported to Region of Interest (ROI) and used as input for further spectral processing.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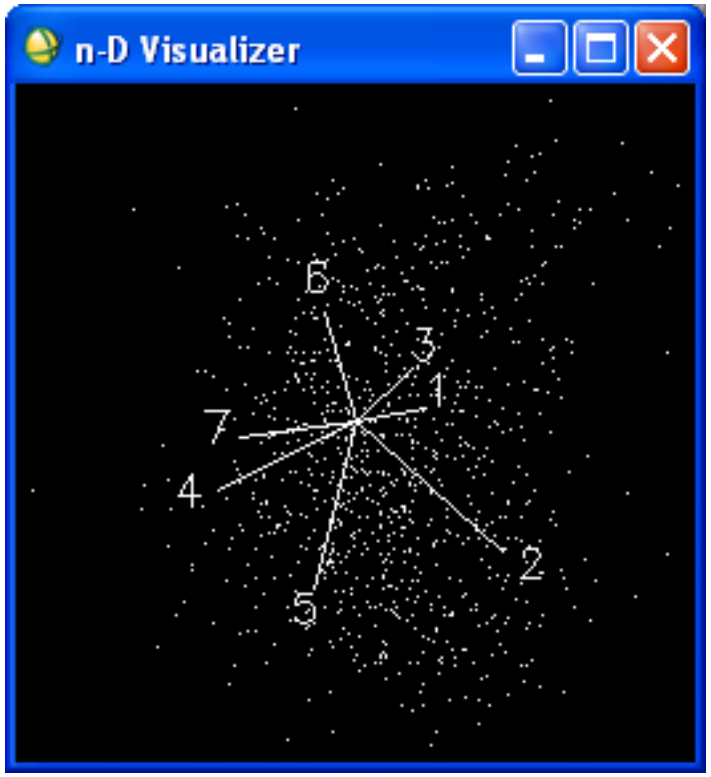
n-D Visualizer
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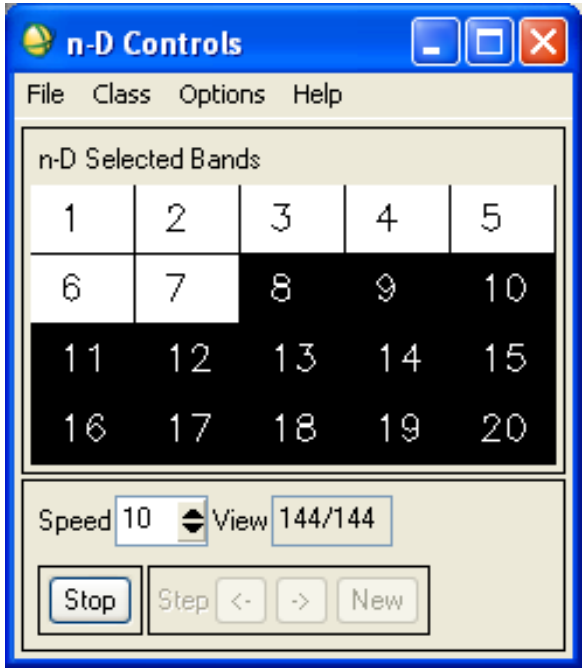
n-D Controls
File
Class
Options
Help
n-D Selected Bands
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6 7 8 9 10
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16 17 18 19 20
Speed 10
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Stop
Step
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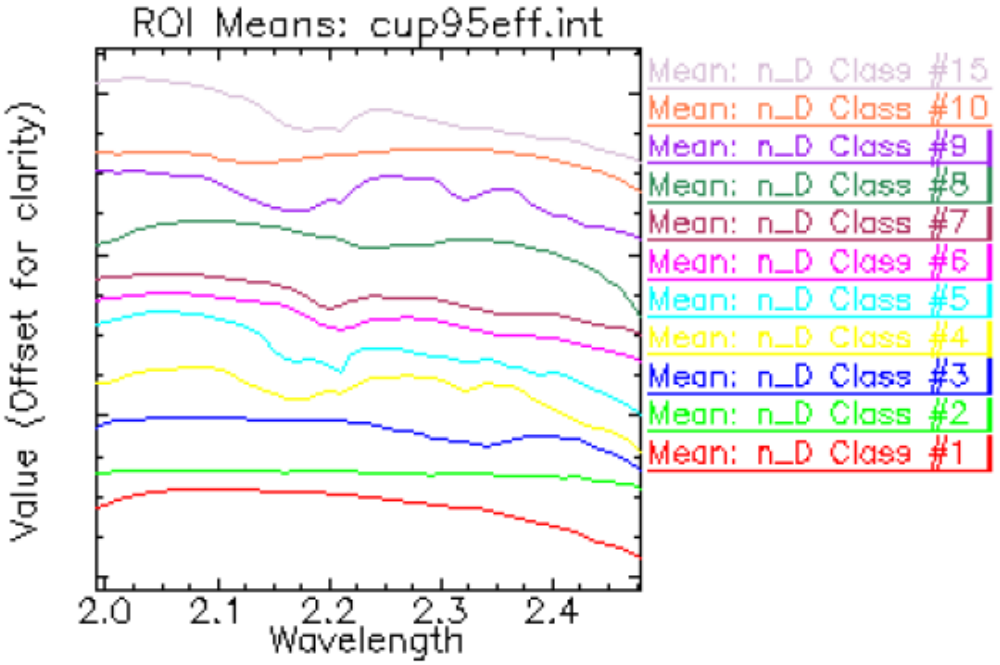
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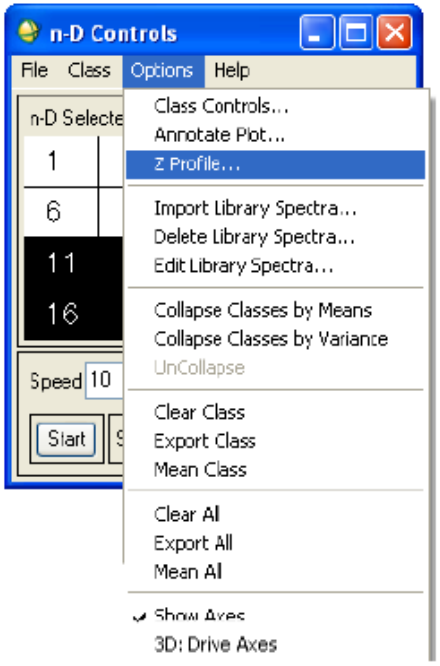
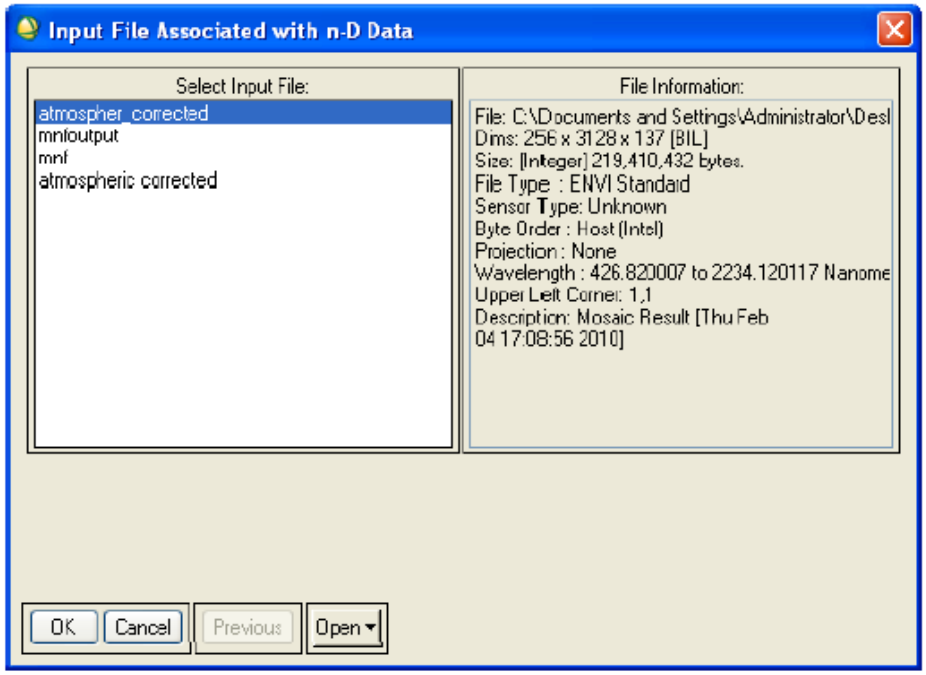
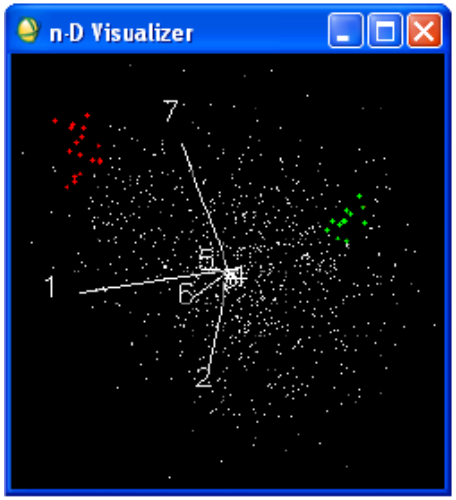
2.1
2.2
2.3
2.4
Wavelength
Mean: n_D Class #15
Mean: n_D Class #10
Mean: n_D Class #9
Mean: n_D Class #8
Mean: n_D Class #7
Mean: n_D Class #6
Mean: n_D Class #5
Mean: n_D Class #4
Mean: n_D Class #3
Mean: n_D Class #2
Mean: n_D Class #1


n-D Controls
File
Class
Options
Help
n-D Selecte
1
6
11
16
Speed 10
Start
Class Controls...
Annotate Plot...
Z Profile...
Import Library Spectra...
Delete Library Spectra...
Edit Library Spectra...
Collapse Classes by Means
Collapse Classes by Variance
UnCollapse
Clear Class
Export Class
Mean Class
Clear All
Export All
Mean All
3D: Drive Axes


Input File Associated with n-D Data
Select Input File:
atmospher_corrected
mnfoutput
mnf
atmospheric corrected
File Information:
File: C:\Documents and Settings\Administrator\Desl
Dims: 256 x 3128 x 137 [BIL]
Size: [Integer] 219,410,432 bytes.
File Type : ENVI Standard
Sensor Type: Unknown
Byte Order : Host (Intel)
Projection : None
Wavelength : 426.820007 to 2234.120117 Nanome
Upper Left Corner: 1,1
Description: Mosaic Result [Thu Feb
04 17:08:56 2010]
OK
Cancel
Previous
Open


n-D Visualizer
7
1
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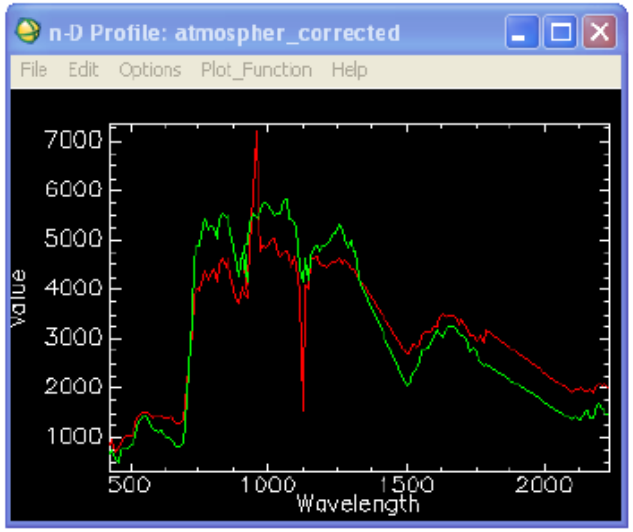
n-D Profile: atmospher_corrected
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Options
Plot_Function
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6000
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3000
2000
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Value
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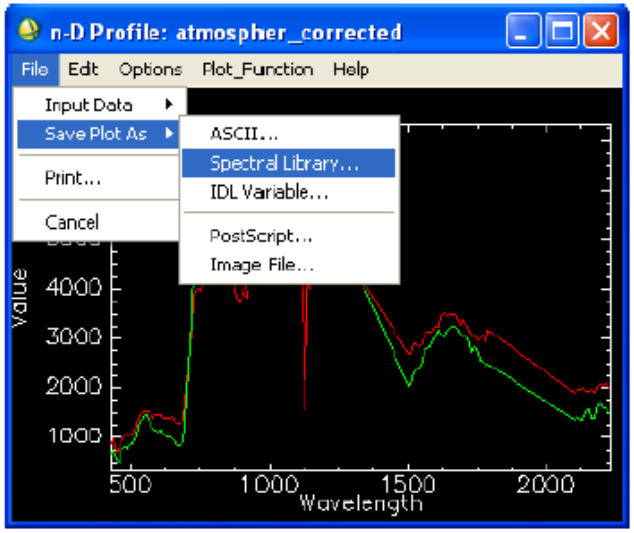
Wavelength


n-D Profile: atmospher_corrected
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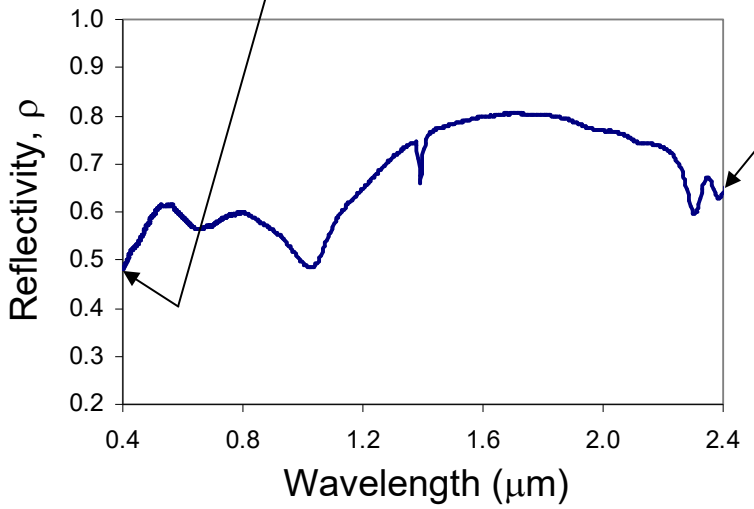
Options
Plot_Function
Help
Input Data
Save Plot As
Print...
Cancel
ASCII...
Spectral Library...
IDL Variable...
PostScript...
Image File...
4000
3000
2000
1000
Value
500
1000
1500
2000
Wavelength

The n-D Space — Where Many Algorithms Operate

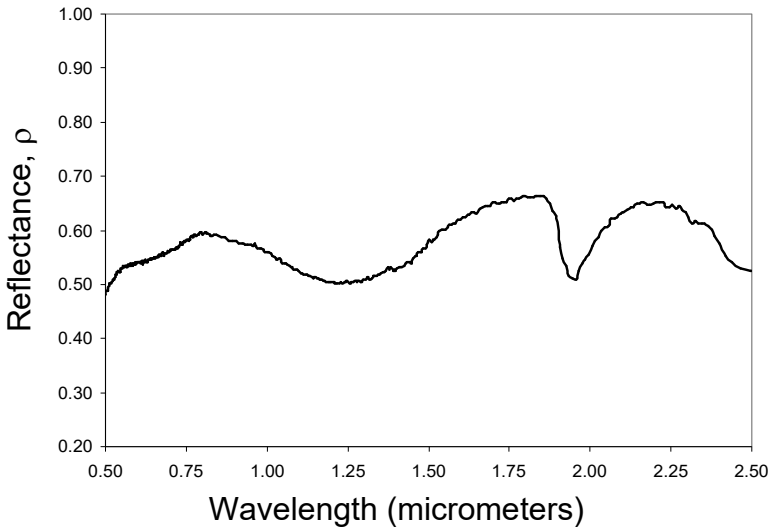
Each HSI spectrum (or pixel) is an n-D vector that can be represented as a single point in n-D space. n-D space is actually where many of our algorithms operate.

$$\text{Spectrum}\,(\text{or pixel}) = [\rho_1, \rho_2, \rho_3, \rho_4, \rho_5, \rho_6, \rho_7, \ldots, \rho_n]^T$$

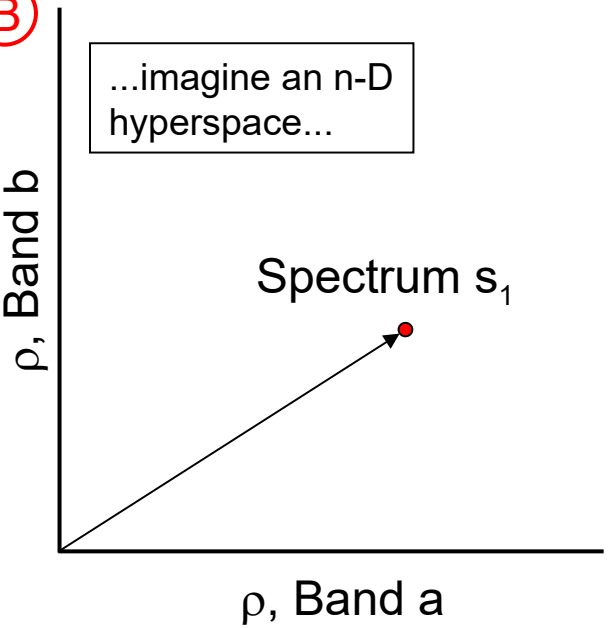


Four (A-D) Equivalent Notations/Representations

Ⓐ



Ⓑ

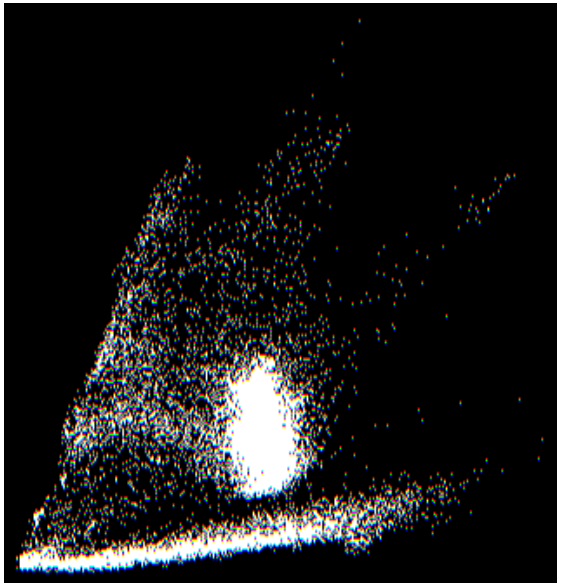


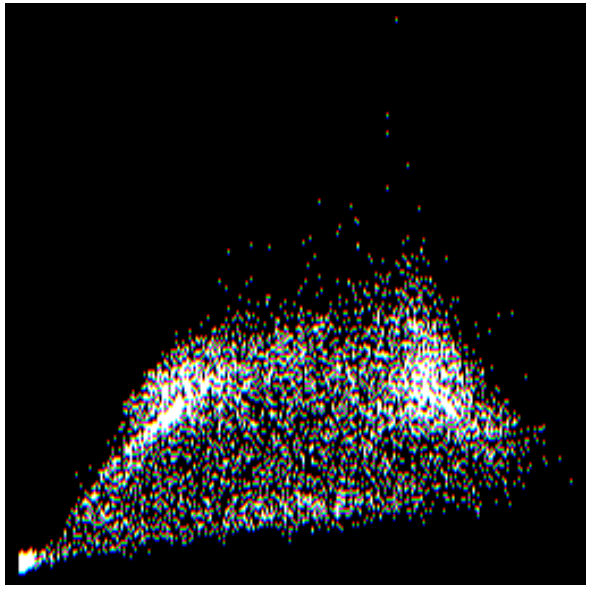
Ⓒ (0.11, 0.23, 0.30, 0.25, 0.16, 0.27, 0.31, 0.37,...,)

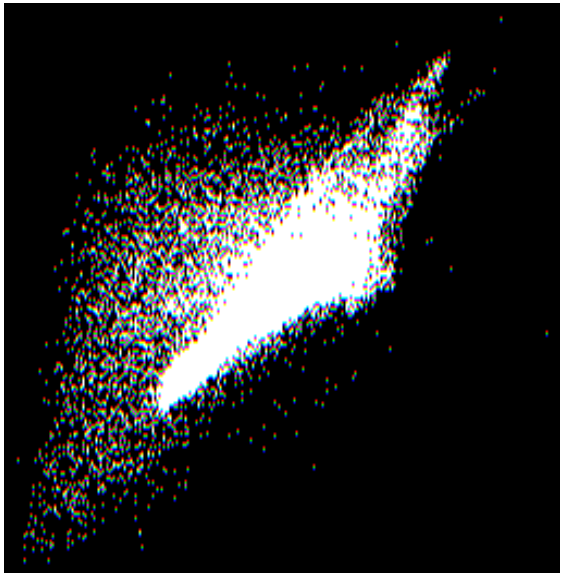
Ⓓ

$$0.11\hat{i} + 0.23\hat{j} + 0.30\hat{k} + 0.25\hat{l} + 0.16\hat{m} + 0.27\hat{n} + 0.31\hat{o} + 0.37\hat{p} + ... +$$

Some HSI Scatter Plots; Spectra as Points in ‘Hyperspace’








Classification Techniques

1. Full Pixel

2.Sub Pixel

Full Pixel or per pixel classification

Full-pixel analysis methods attempt to determine whther one or more target materials are abundant within each pixel in the image on the basis of the spectral similarity between the training (reference) pixel and target (unknown) spectra Spectral Angle Mapper

1. **Spectral Feature Fitting**

2. **Support Vector Machines**

Spectral Angle Mapper or SAM

The spectral angle is the angle between any two vectors originating from a common origin. The magnitude of the angle indicates the similarity or dissimilarity of the materials—a smaller angle correlates to a more similar spectral signature.

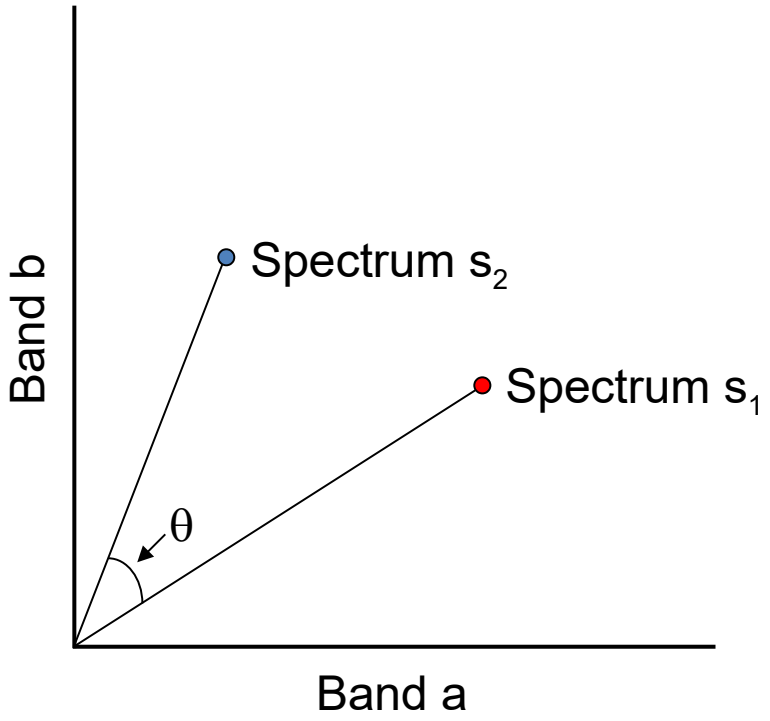
This method is relatively insensitive to changes in illumination on the target material because changes in light will impact the magnitude but not the direction of the vector. A poorly illuminated target will cause the points to be plotted closer to the origin

SAM: n-D Geometry

Angular Distance Metric (Spectral Angle Mapper or SAM)

Assume a two band spectral remote sensing system. Each two point 'spectrum' is a point in Band b vs. Band a space.

A 2D scatterplot with 2 spectra:

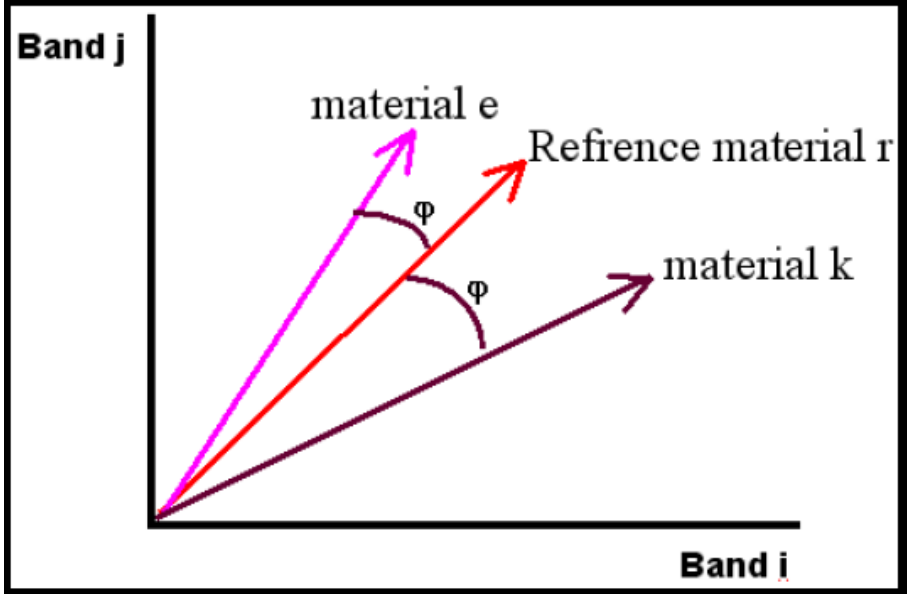


The angle, θ, between the two lines connecting each spectrum (point) to the origin is the angular separation of the two spectra. Smaller angular separations indicate more similar spectra.

Spectral Angle Mapper – SAM

SAM algorithm Compares Unlabeled pixel With Reference spectra in *n* dimensions

Reference spectra may be obtained from Ground based spectroradiometer measurements OR Image endmembers

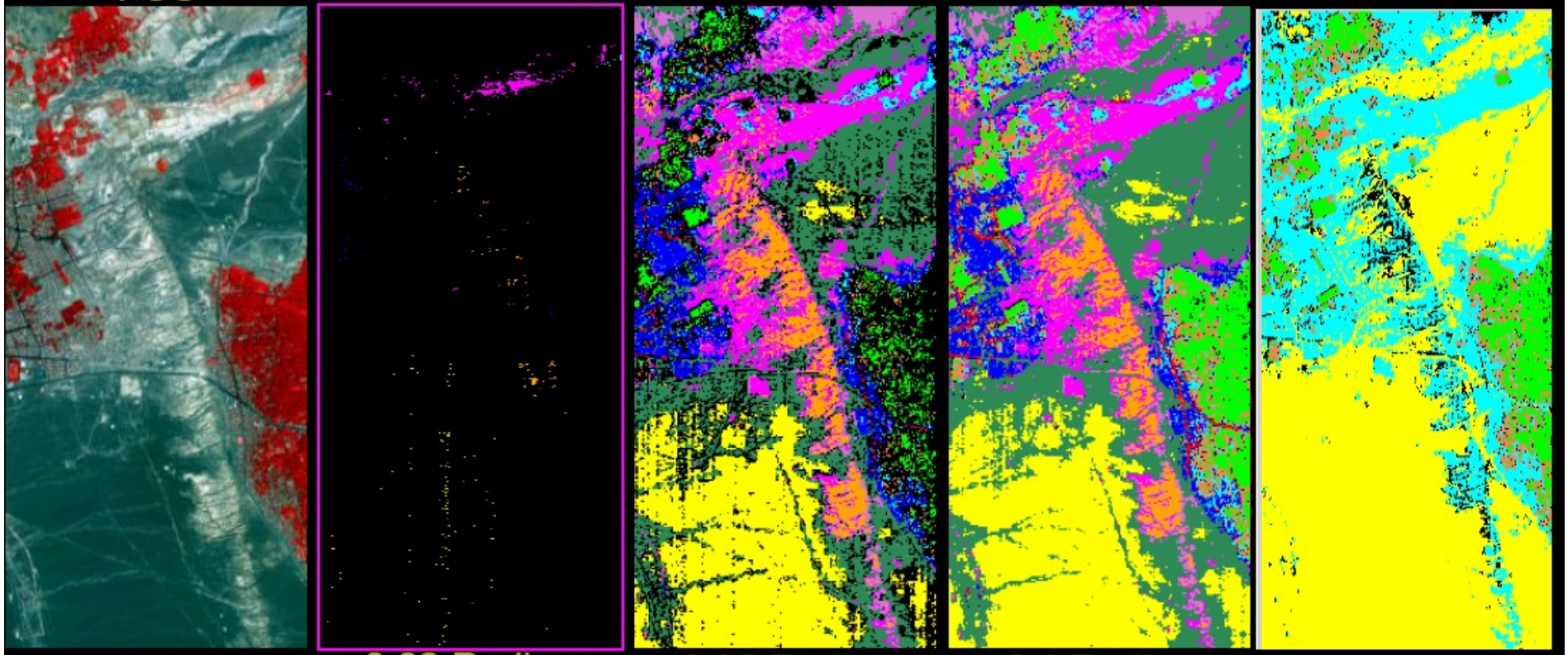


$$\cos\varphi = \frac{\sum_{i=0}^{n} e_i r_i}{\sqrt{\sum_{i=0}^{n} e_i^2}\sqrt{\sum_{i=0}^{n} r_i^2}}$$

φ = spectral angle
e = given image spectra
r = reference spectra (endmember)
n = number of bands

FCC

SAM classified image with different Radians



0.02 Radians

0.05 Radians

0.1 Radians

> 0.1 Radians

Vegetation
Clinoptilolite
Desert Pavement
Kaolinite
Montmorillonite
Sepiolite
Settlement
Yellow-tan to orange brown siltstones and sandstone
Well bedded ash-flow tuffs (mainly trachyandesitic and basaltic)
Buff to light brown-fan silts and argillaceous sandstone

0.1 Radians

With

few classes

Misclassification

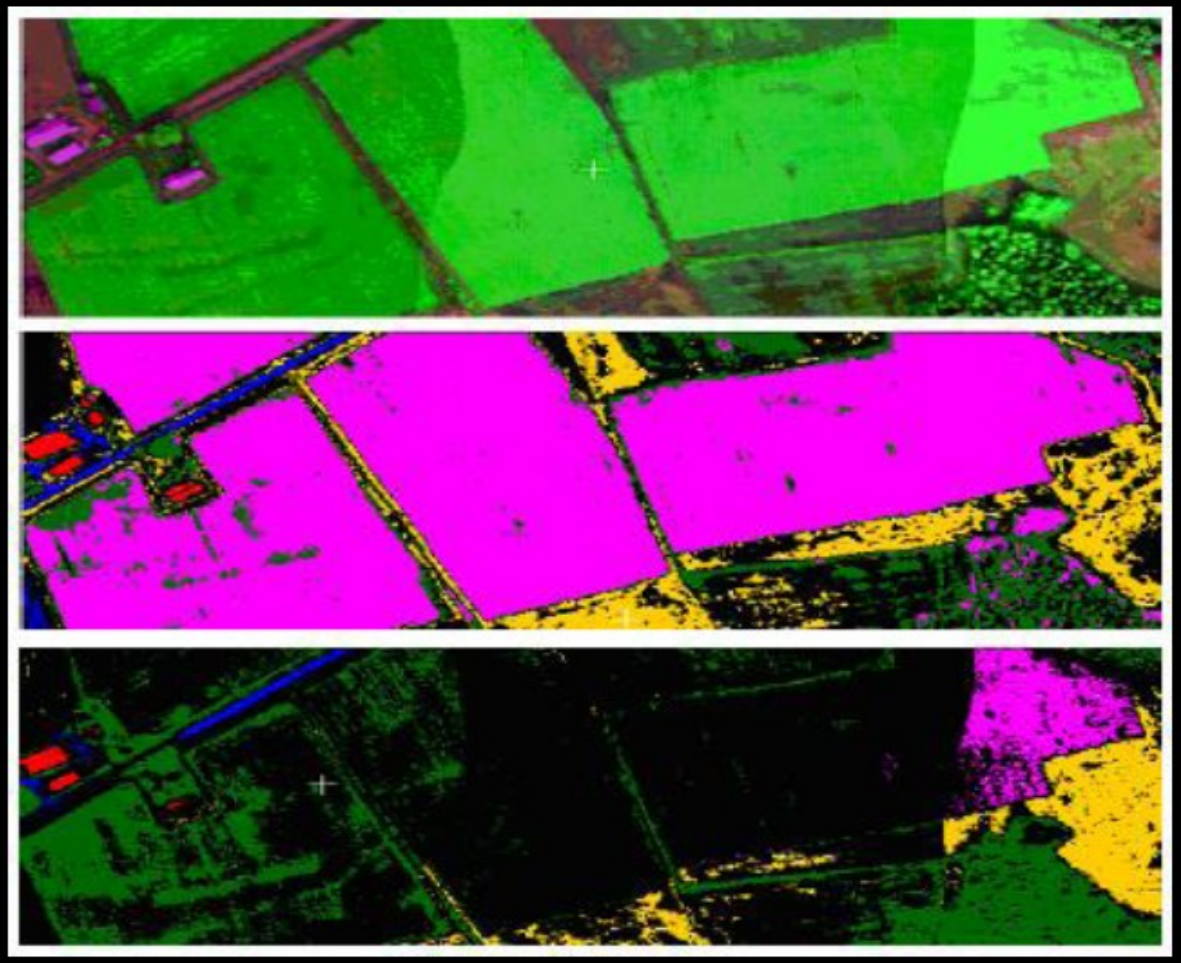
Pixel Population

Class	SAM Angle (radians)		
	0.02	0.05	0.10
	Pixel Population (%)		
Vegetation	0.001	0.797	2.333
Clinoptilolite	0.047	18.951	23.184
Desert Pavement	0.231	46.126	55.429
Kaolinite	0.004	0.101	0.264
Montmorillonite	0.008	0.732	1.398
Sepiolite	0.000	0.290	1.507
Well bedded ash-flow tuffs (mainly trachyandesitic and basaltic lavas)	0.000	0.268	1.289
Settlement	0.015	2.275	2.534
Road	0.000	0.087	0.636
Yellow-tan to orange brown siltstones and sandstone	0.043	1.551	1.681
Well bedded ash-flow tuffs (mainly trachyandesitic and basaltic)	0.028	3.085	3.988
Buff to light brown-fan silts and argillaceous sandstone	0.148	4.949	5.198
Unclassified	99.476	20.789	0.558

Smaller the angle – closer to reference spectra – fewer will be the population

Too large an angle – Away from reference spectra - Misclassification

SAM - Illumination



Variance in illumination (up)

Spectral Angle Mapper (middle)

Maximum Likelihood (down)

Variation in illumination affected more strongly when the Maximum Likelihood and Minimum Distance were used. The results of the classification deteriorated fast while the Spectral Angle Mapper and the Spectral Correlation Mapper were better in that case.

Spectral Correlation Mapper

$$R = \frac{\sum (X - \overline{X})(Y - \overline{Y})}{\sqrt{\sum (X - \overline{X})^2 \sum (Y - \overline{Y})^2}}$$

X = Image Spectrum (DN value) of the pixel in all spectral bands

$\overline{X}$ = Mean of the DN values of the same pixel over all spectral bands

Y= Reference Spectrum of a class in all spectral bands

$\overline{Y}$ = Mean of the reference spectra of a class over all spectral bands

1. Aim is to classify pixel X

2. Given DN value of pixel X for every band

3. Use

$$R = \frac{\sum (X - \overline{X})(Y - \overline{Y})}{\sqrt{\sum (X - \overline{X})^2 \sum (Y - \overline{Y})^2}}$$

to determine R for each class

4. Assign the pixel to the class where the value of R is maximum

SCM Classified Image

Classified Image

Overall Accuracy: ~95%

Original Image

Support Vector Machine

SVM performs classification by constructing an N-dimensional hyper plane that optimally separates the data into two categories

Support vector Machines are good candidates for remote sensing classification in particular hyperspectral image classification in many ways

1.SVM can work well small training data set
2.SVM perform with high classification accuracy for data having hundreds of dimension as in hyperspectral images
3.The structure of SVM is less complex even with high dimensional data

The SVM aim to maximize the margin between two classes of interest by placing linear separating hyperplane

The SVM uses structural risk minimization (SRM). The Empirical risk minimizes the misclassification error and whereas structural risk minimization minimizes the probability of misclassification.

Support Vector Machine

A set of features that describes one case (i.e., a row of predictor values) is called a vector. So the goal of SVM modeling is to find the optimal hyperplane that separates clusters of vector in such a way that cases with one category of the target variable are on one side of the plane and cases with the other category are on the other size of the plane.

The vectors near the hyperplane are the support vectors. The figure below presents an overview of the SVM process.

The points lying on the two parallel hyperplanes are called Support Vector (SV). The margin is defined as the Euclidian distance between the Support vector and Optimal separating hyperplane (OSH). Maximization of margin ensures better generalization capability for the test data

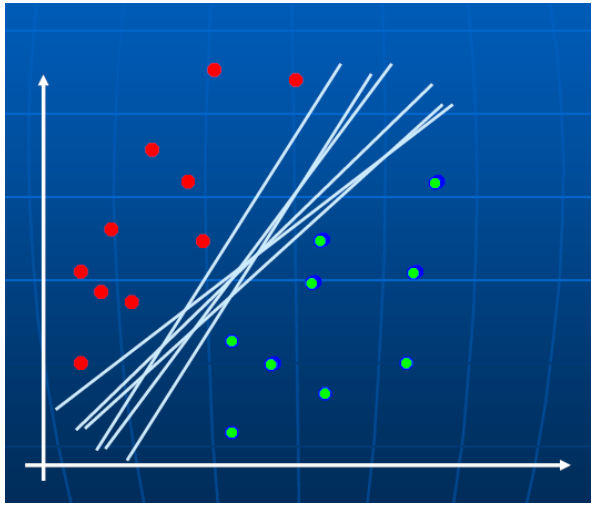
SVM are based on the structural risk minimization (SRM) which aims at minimizing the upper bound of the expected error over the whole data set.

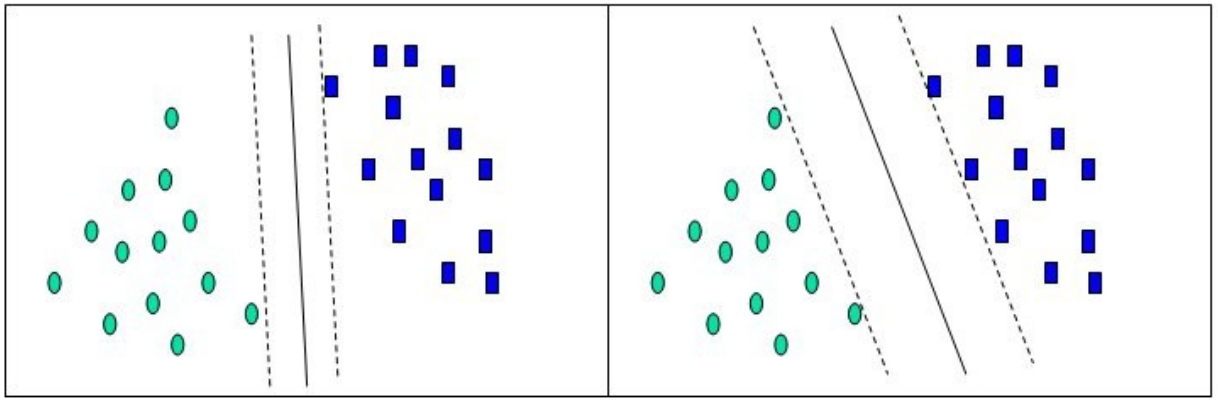
The advantage of SVM is its ability to work with smaller training data sets, SVM are becoming preferred classification method to classify hyperspectral imagery

A Two-Dimensional Example

Before considering *N*-dimensional hyperplanes, let's look at a simple 2-dimensional example. Assume we wish to perform a classification, and our data has a categorical target variable with two categories.

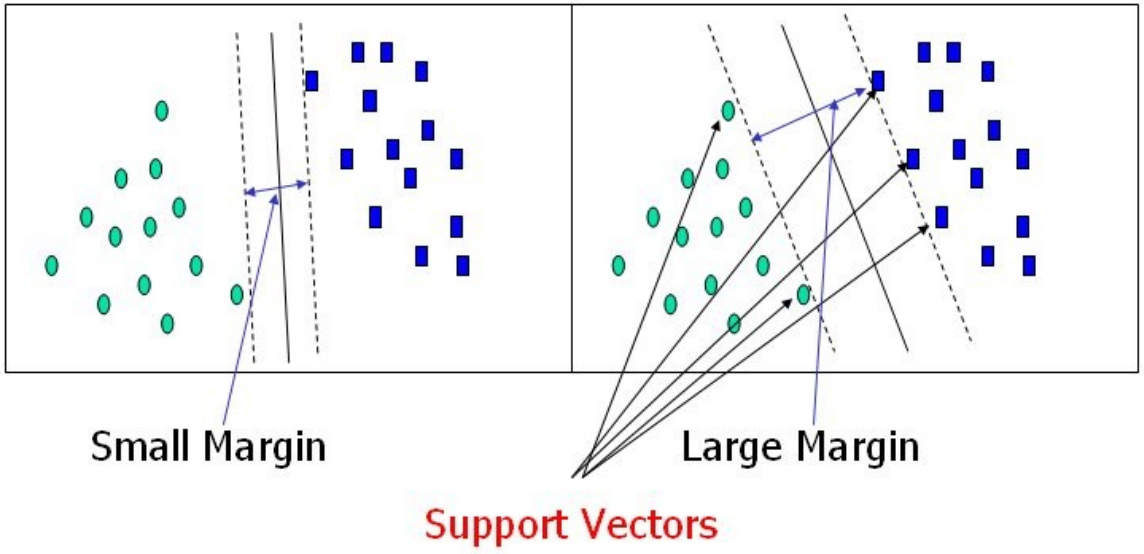
Also assume that there are two predictor variables with continuous values. If we plot the data points using the value of one predictor on the X axis and the other on the Y axis we might end up with an image such as shown below. One category of the target variable is represented by rectangles while the other category is represented by ovals.





In this idealized example, the cases with one category are in the lower left corner and the cases with the other category are in the upper right corner; the cases are completely separated. The SVM analysis attempts to find a 1-dimensional hyperplane (i.e. a line) that separates the cases based on their target categories. There are an infinite number of possible lines; two candidate lines are shown above. The question is which line is better, and how do we define the optimal line.

The dashed lines drawn parallel to the separating line mark the distance between the dividing line and the closest vectors to the line. The distance between the dashed lines is called the *margin*. The vectors (points) that constrain the width of the margin are the *support vectors*. The following figure illustrates this.

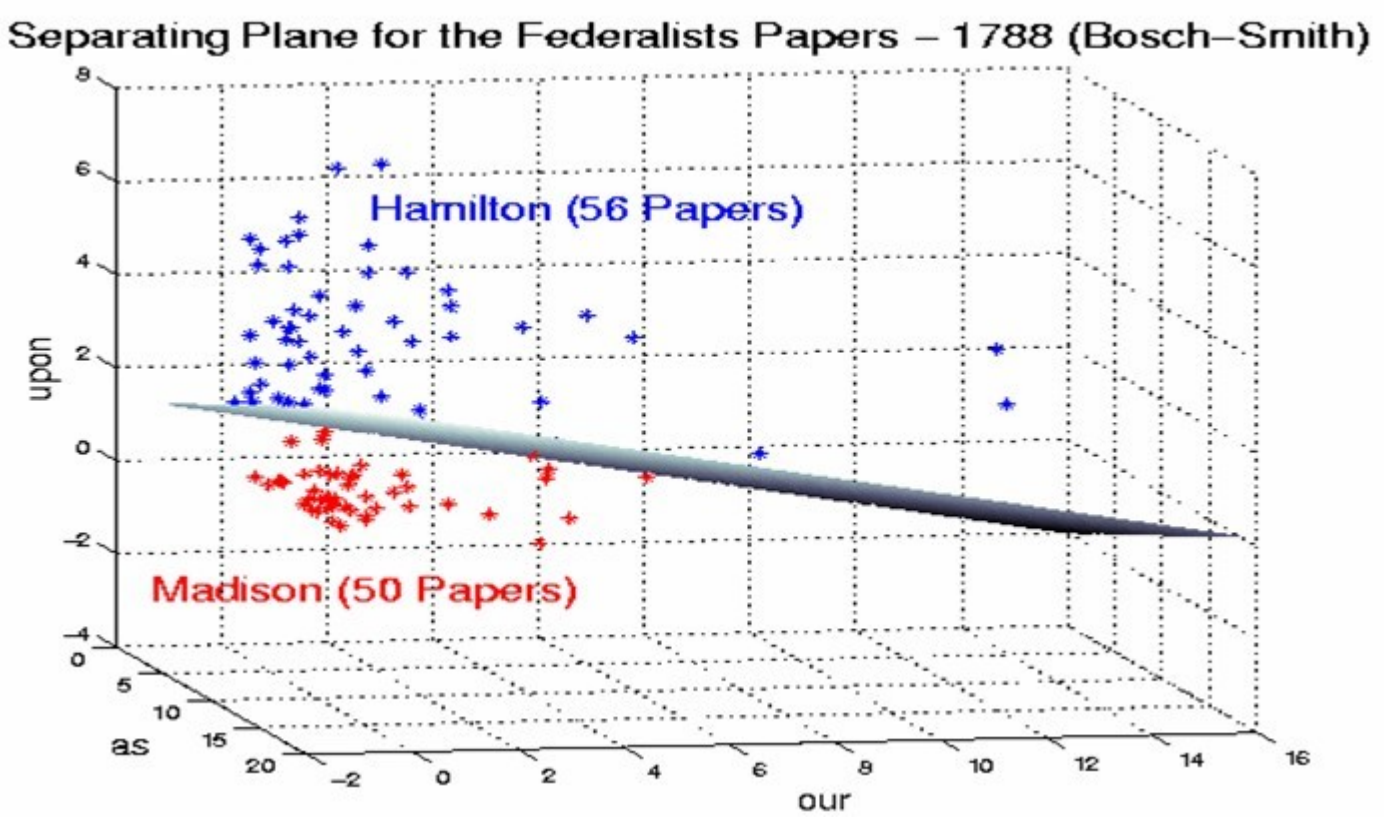


An SVM analysis finds the line (or, in general, hyperplane) that is oriented so that the margin between the support vectors is maximized. In the figure above, the line in the right panel is superior to the line in the left panel.

If all analyses consisted of two-category target variables with two predictor variables, and the cluster of points could be divided by a straight line, it would be easy. Unfortunately, this is not generally the case, so SVM must deal with (a) more than two predictor variables, (b) separating the points with non-linear curves, (c) handling the cases where clusters cannot be completely separated, and (d) handling classifications with more than two categories.

Flying High on Hyperplanes

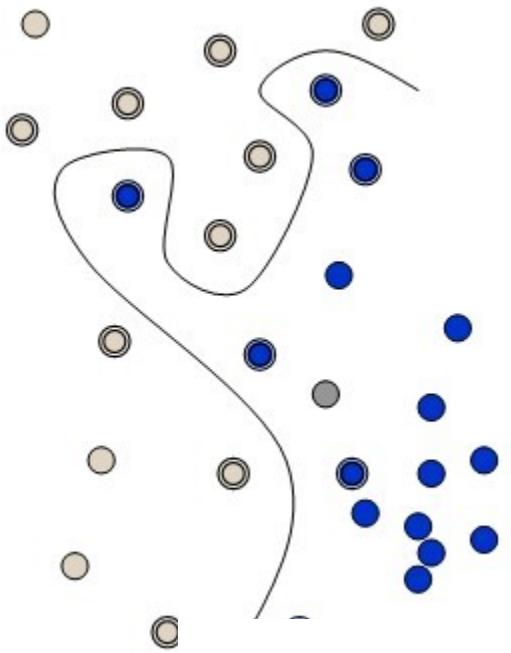
In the previous example, we had only two predictor variables, and we were able to plot the points on a 2-dimensional plane. If we add a third predictor variable, then we can use its value for a third dimension and plot the points in a 3-dimensional cube. Points on a 2-dimensional plane can be separated by a 1-dimensional line. Similarly, points in a 3-dimensional cube can be separated by a 2-dimensional plane.



As we add additional predictor variables (attributes), the data points can be represented in *N*-dimensional space, and a (N-1)-dimensional hyperplane can separate them.

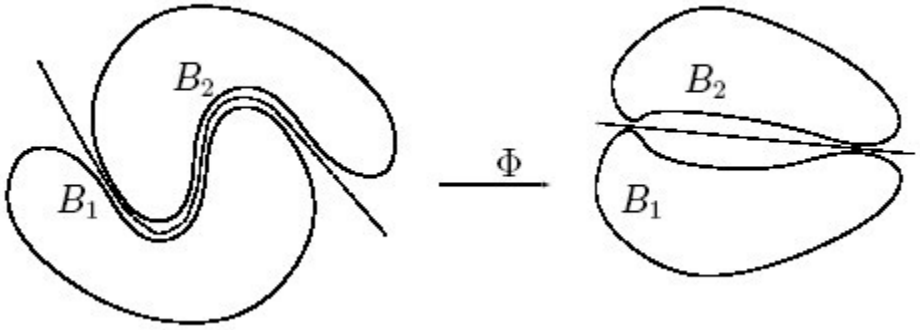
When Straight Lines Go Crooked

The simplest way to divide two groups is with a straight line, flat plane or an N-dimensional hyperplane. But what if the points are separated by a nonlinear region such as shown below?



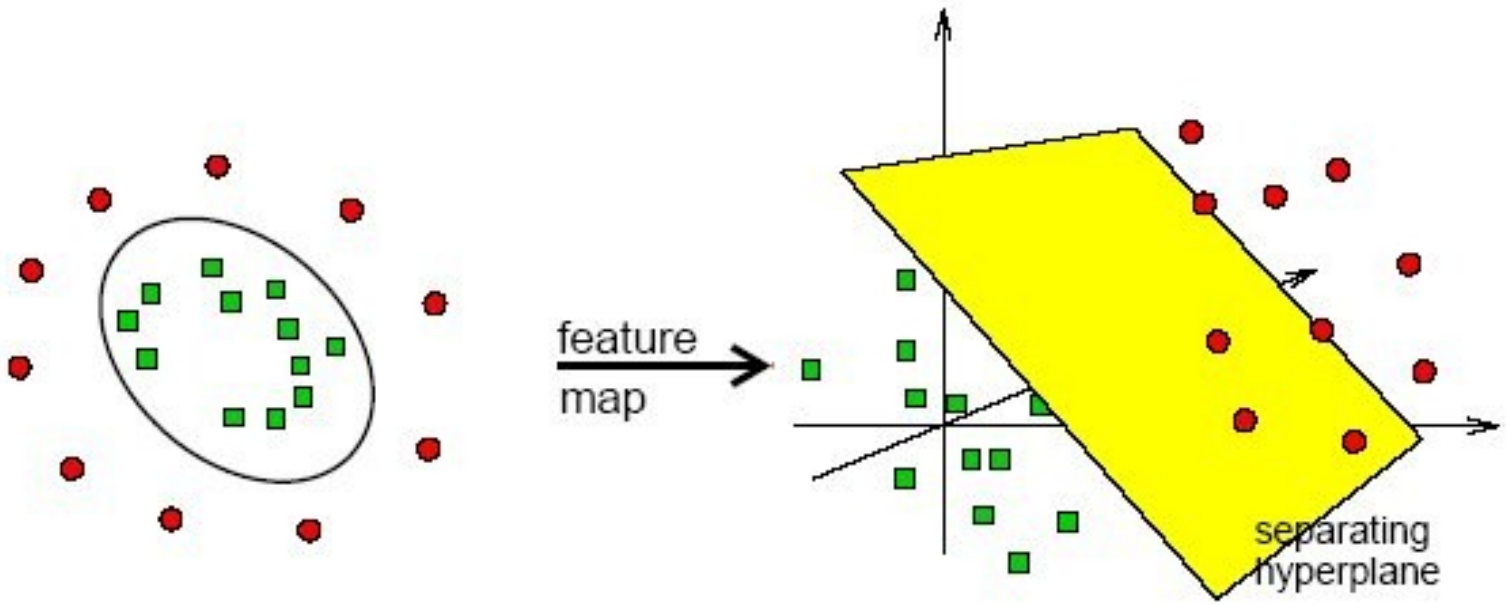
In this case we need a nonlinear dividing line.

Rather than fitting nonlinear curves to the data, SVM handles this by using a kernel function to map the data into a different space where a hyperplane can be used to do the separation.



The kernel function may transform the data into a higher dimensional space to make it possible to perform the separation.

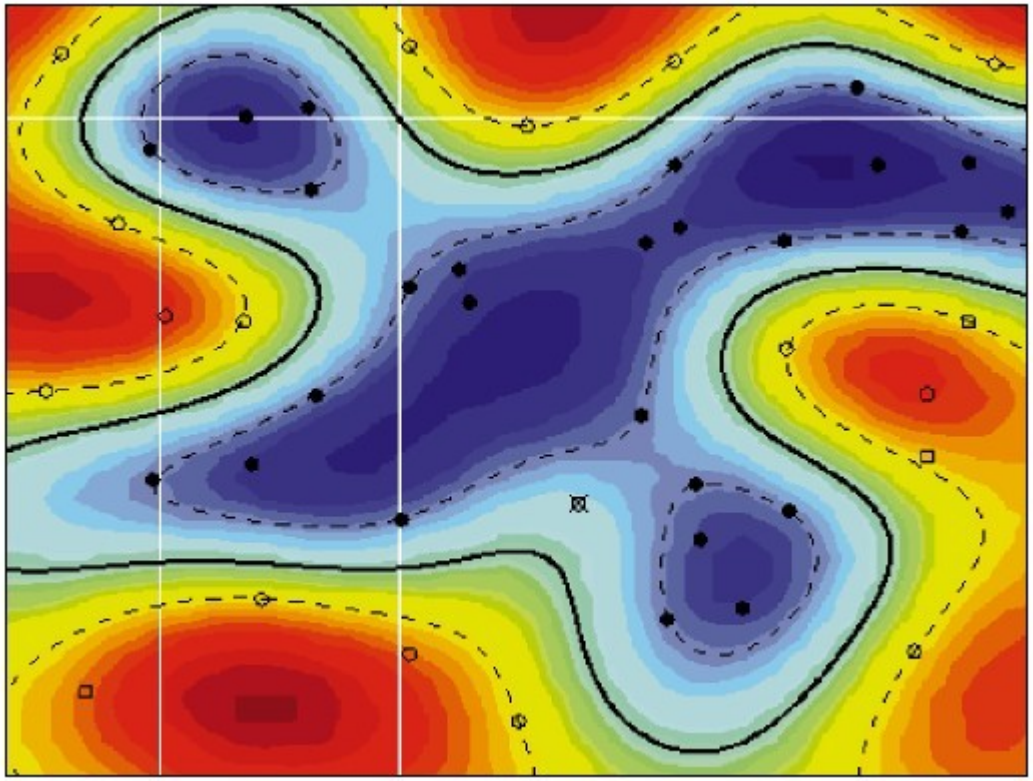
Separation may be easier in higher dimensions



complex in low dimensions

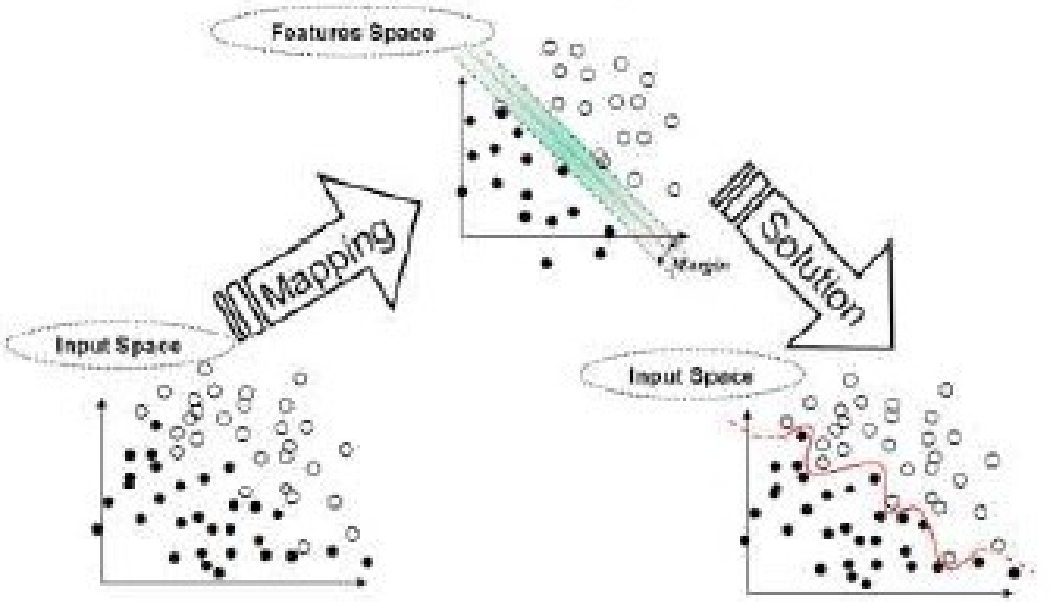
simple in higher dimensions

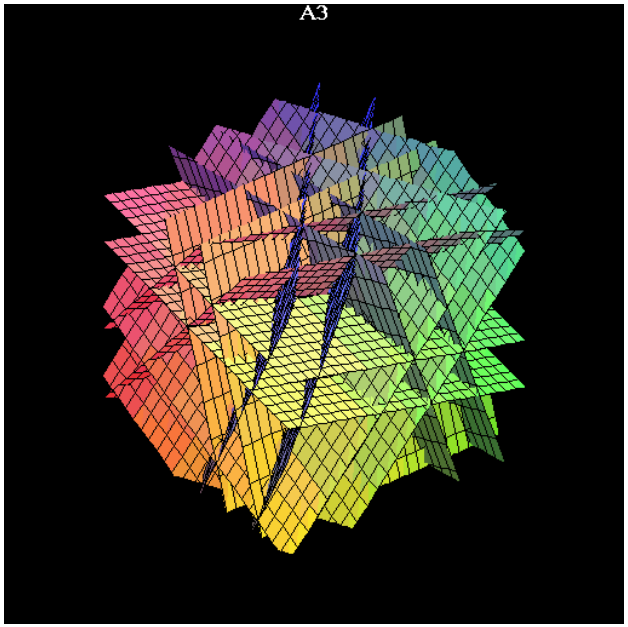
The concept of a kernel mapping function is very powerful. It allows SVM models to perform separations even with very complex boundaries such as shown below

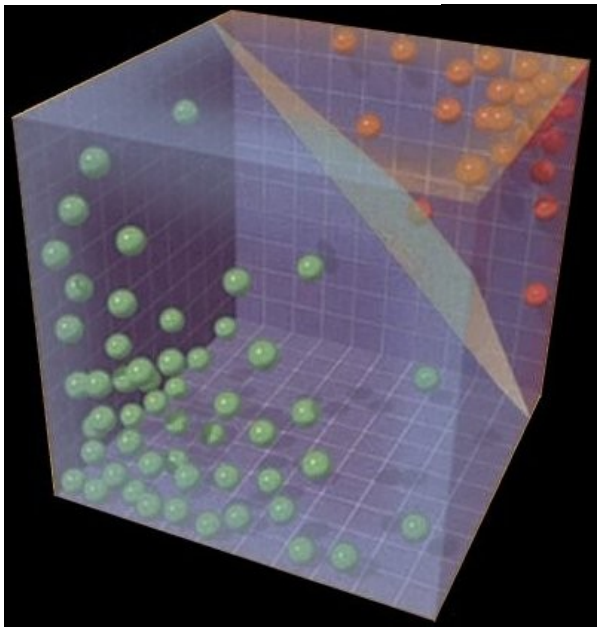


Many kernel mapping functions can be used – probably an infinite number. But a few kernel functions have been found to work well in for a wide variety of applications. The default and recommended kernel function is the Radial Basis Function (RBF).

The SVM algorithm



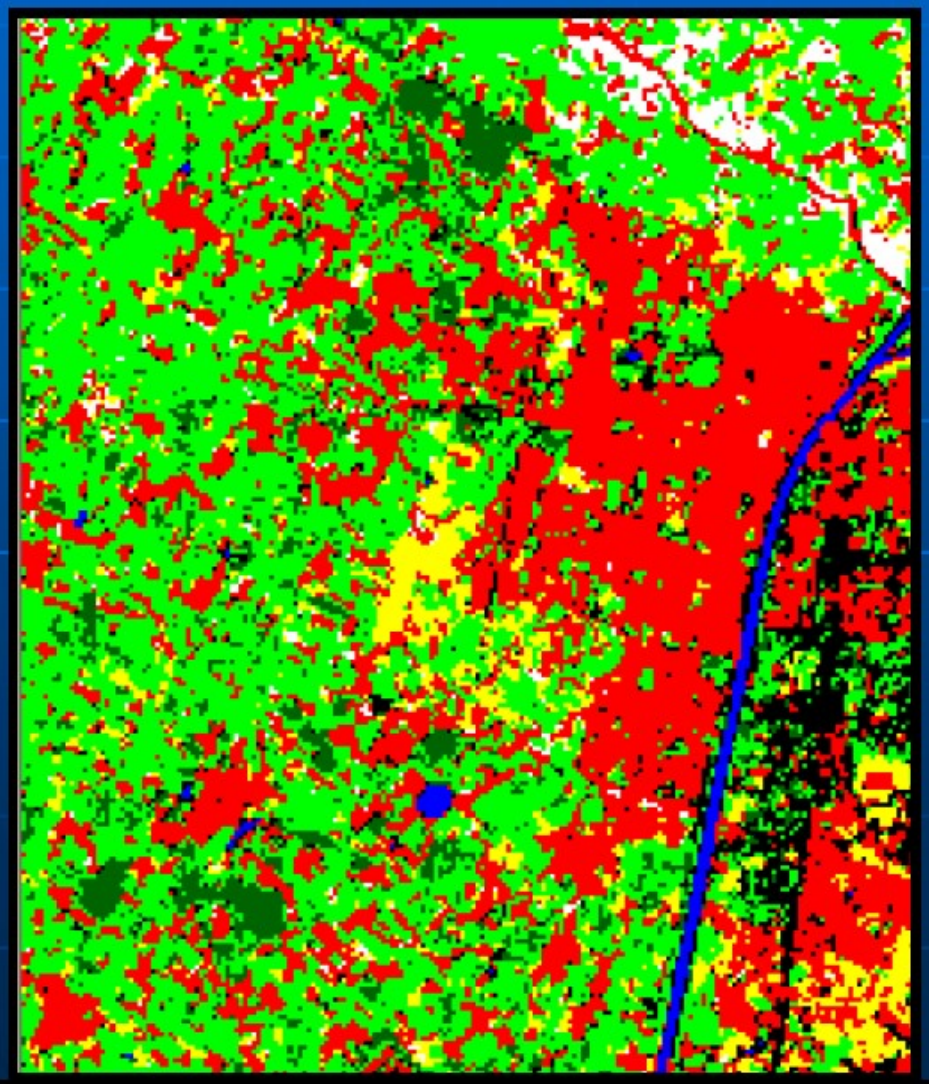




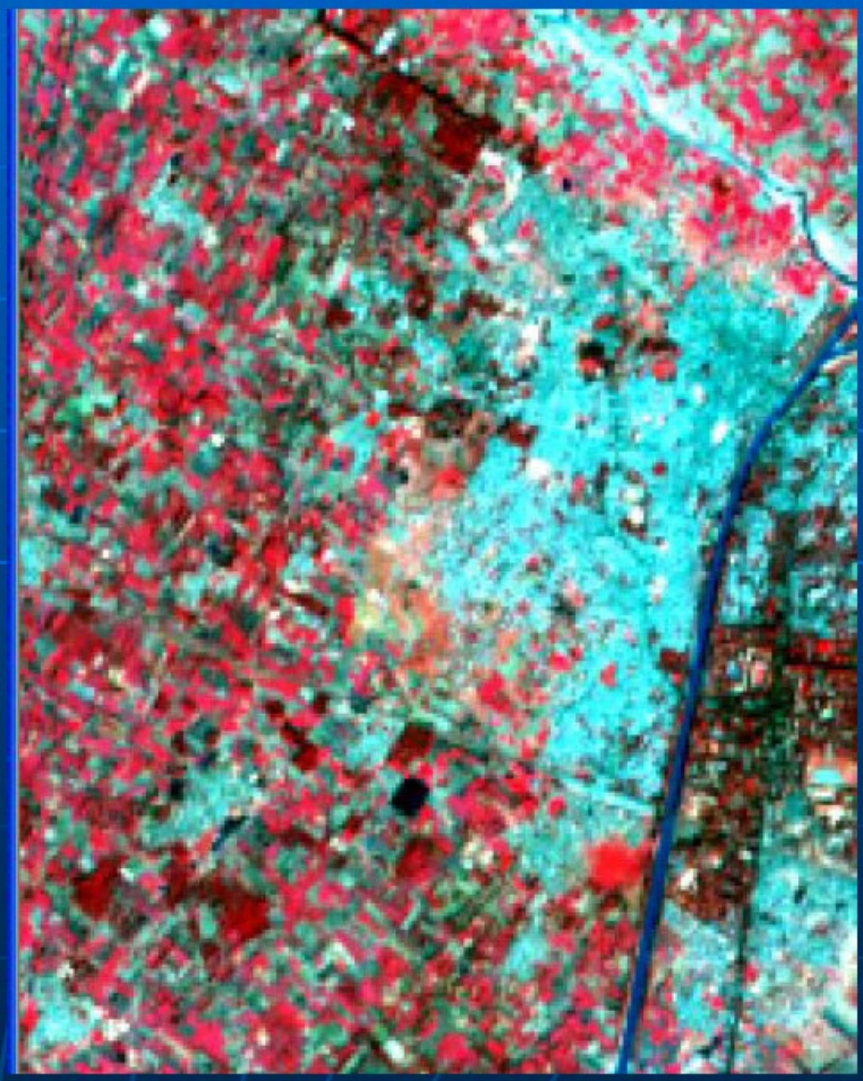
SVM Classified Image

Classified Image

Overall Accuracy: ~98%

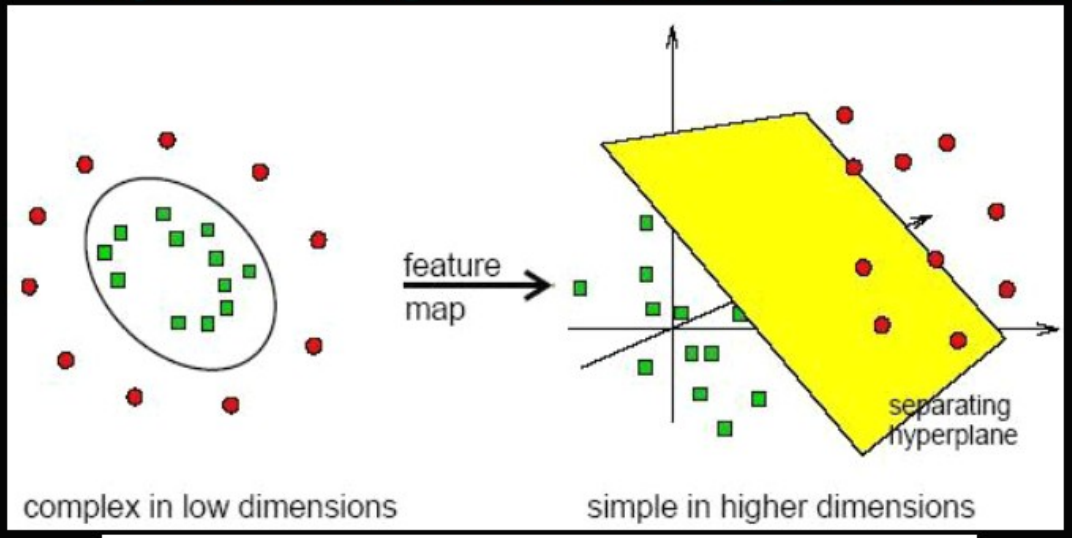


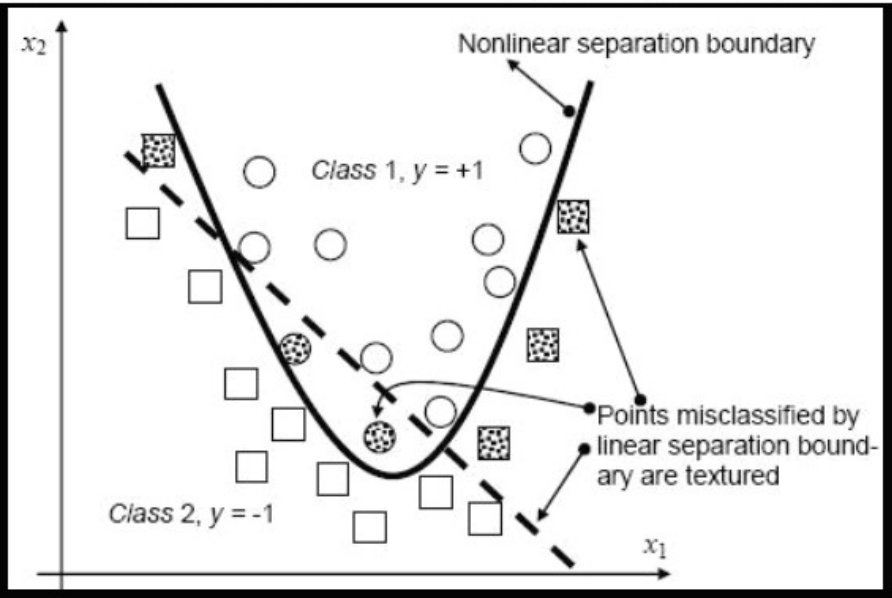
Original Image



Kernel function transforms the data into a higher dimensional space to make it possible to perform the separation

Separation may be easier in higher dimensions





Spectral Feature Fitting

To match target and reference pixel spectra by examining specific absorption features in the spectra (continuum removed spectrum)

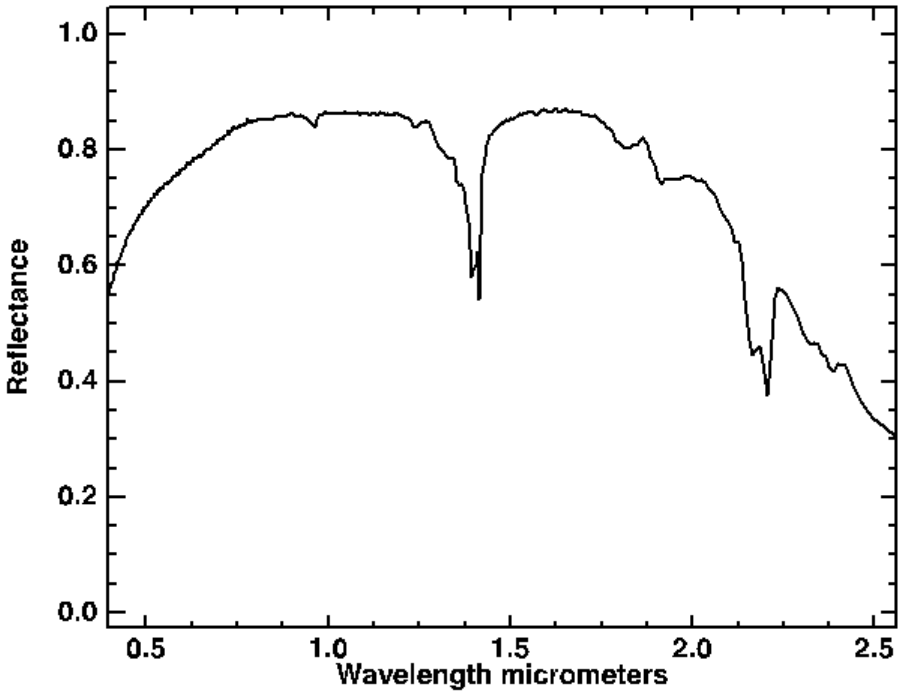
User specifies a range of wavelengths within a unique absorption feature exists for the chosen target

Reference (training) spectra are then compared to the target spectrum using two measurements:

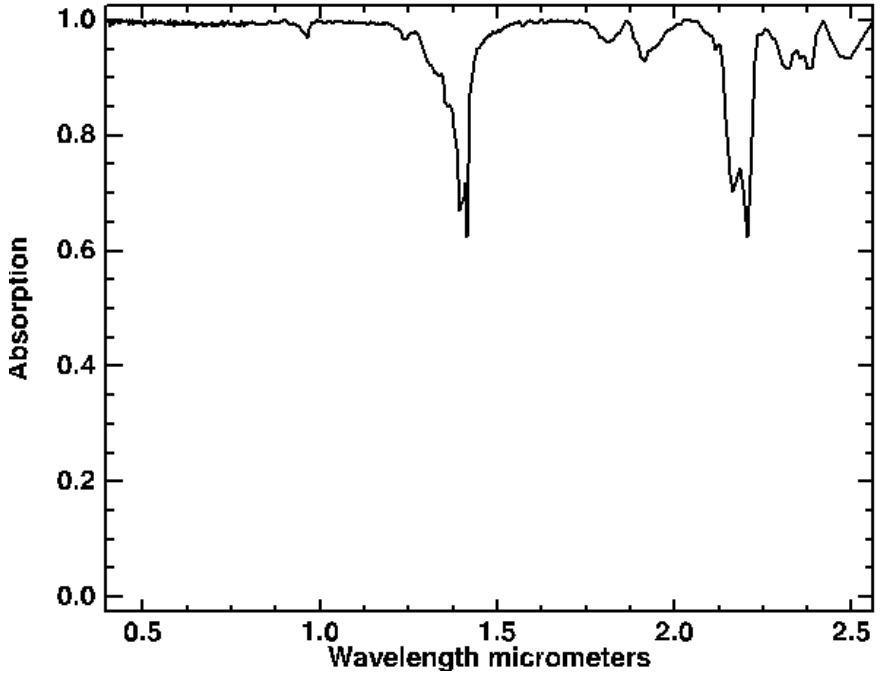
- The depth of the feature in the target is compared to the depth of the feature in the reference, and
- The shape of the feature in the target is compared to the shape of the feature in the reference (using a least-squares technique)

Continuum Removal

- Continuum Removal normalizes reflectance spectra to allow comparison of individual absorption features from a common baseline
- Continuum is a convex hull fit over the top of a spectrum utilizing straight-line segments that connect local spectra maxima
- Continuum is removed by dividing it into the actual spectrum for each pixel in the image
- The resulting image spectra are equal to 1.0 where the continuum and the spectra match and less than 1.0 where absorption features occur



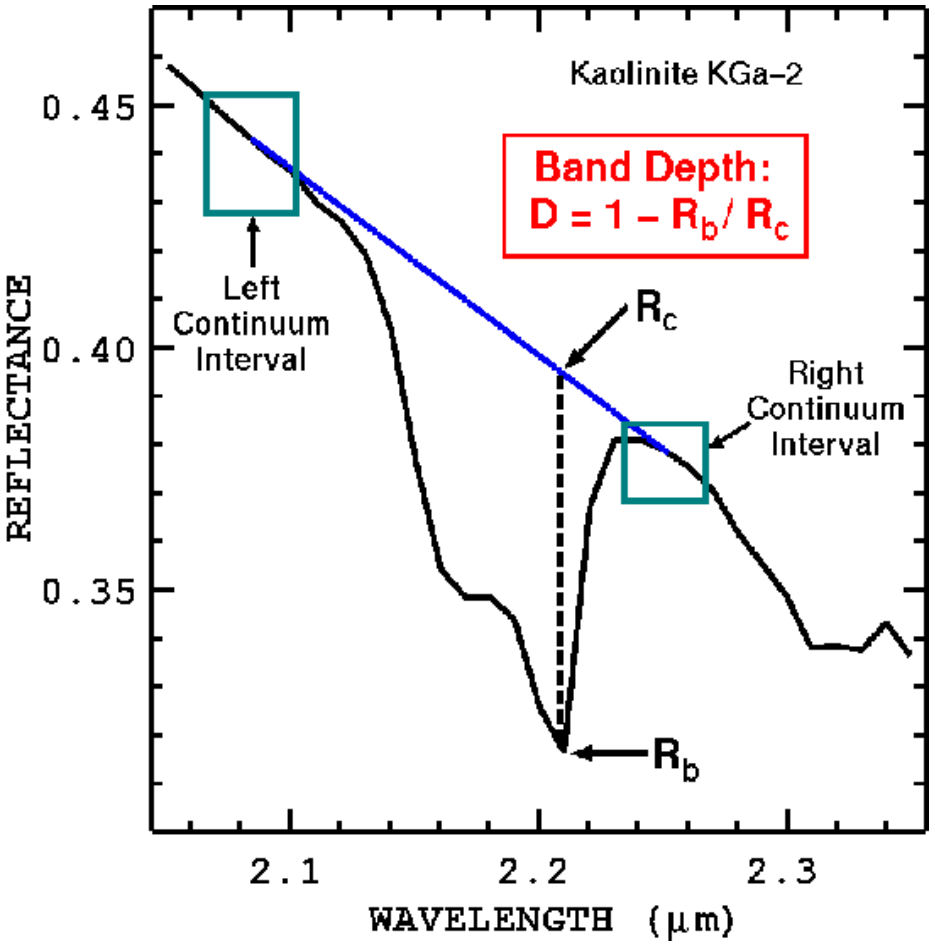
Kaolinite reflectance spectra



Continuum removed spectra

Band depth

The apparent depth of an absorption feature, relative to the surrounding continuum in a reflectance or emittance spectrum



$$D = 1 - R_b / R_c$$

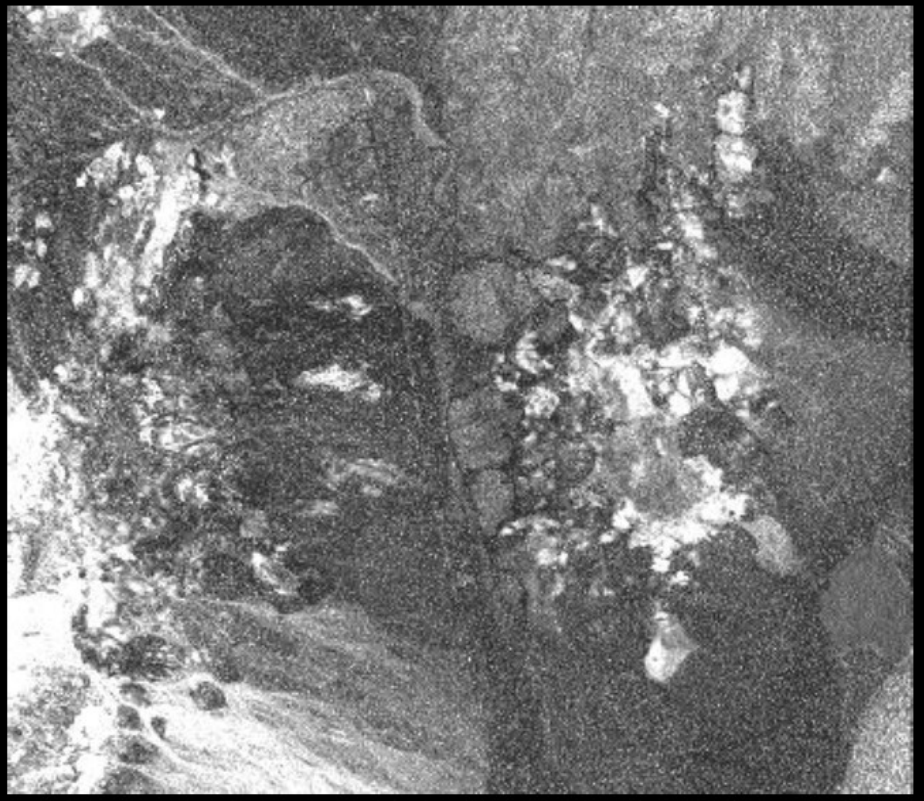
R_b is the reflectance at the absorption-band center (the minimum in the continuum-removed feature), and
R_c is the reflectance value of the continuum at the wavelength of the band center

If the features one is looking for have weak absorption Continuum removal suppresses them

Spectral Feature Fitting Image

Cuprite Nevada, AVIRIS

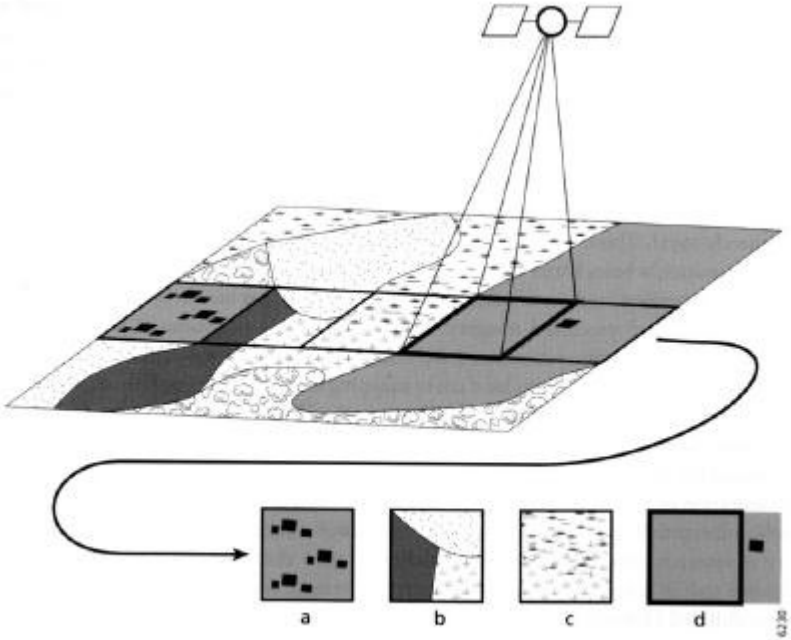
R – 2.1010 µm
G – 2.2008 µm
B – 2.3402 µm



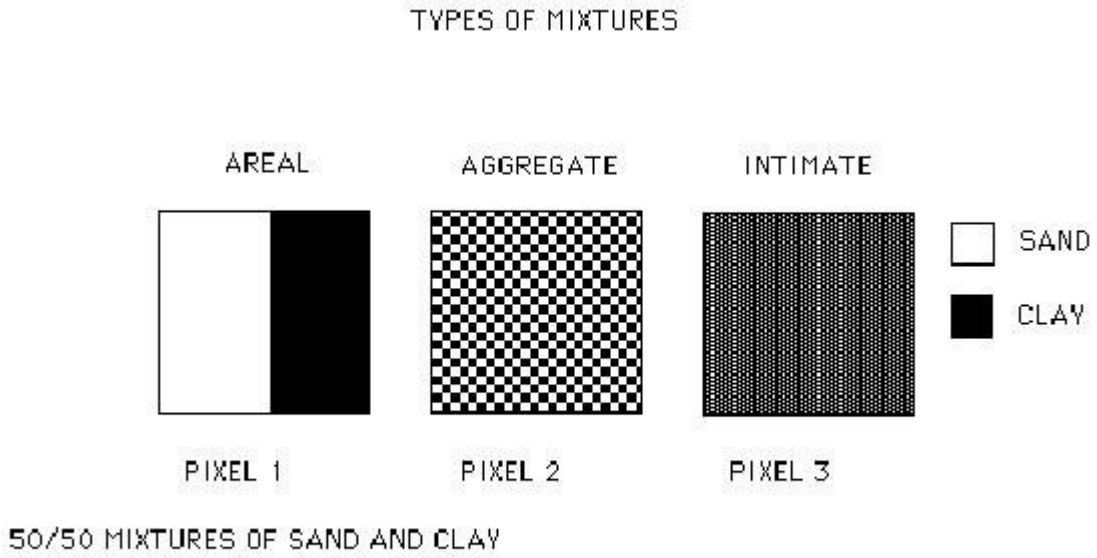
RMS image for Alunite
Bright – good fit ; Dark – Bad Fit

Spectral Unmixing - Sub-Pixel analysis

- Mixed pixels are generated if the size of the pixel includes more than one type of terrain cover
- Measured spectral radiance of a pixel is the integration of the radiance reflected from all the type of terrain covers within the ground instantaneous field of view (GIFOV)
- Spectral mixing is inherent in any finite-resolution digital imagery
- Mixed pixel problem not well addressed with multispectral data because distinctions with limited band numbers were clear to differentiate classes
- Unmixing has particular relevance for something like mineral mapping where abundance of minerals is desired parameter



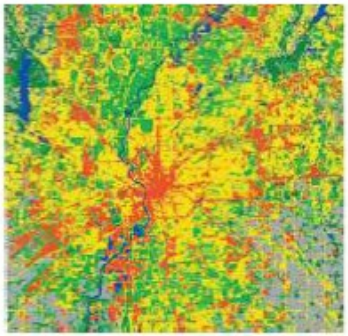
a: Presence of small or sub-pixel targets
b: Presence of boundaries of discrete parcels
c: Gradual transition between land cover classes
d: Contribution of areas outside the area represented by a pixel



Number of outputs for each spatial unit

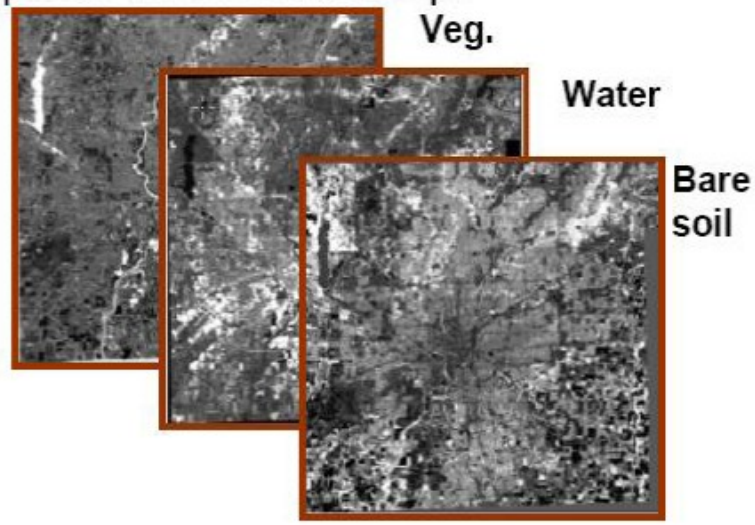
Hard (crisp) classification

each pixel is forced or constrained to show membership to a single class.



Soft (fuzzy) classification

each pixel may display multiple and partial class membership.



Soft classification is an alternative to hard classification because of its ability to deal with **mixed pixels**.

Spectral unmixing Is a procedure by which the measured spectrum of a mixed pixel is decomposed into a collection of constituent spectra, or *endmembers*, and

a set of corresponding fractions, or *abundances*, indicating the proportion of each endmember present in the pixel.

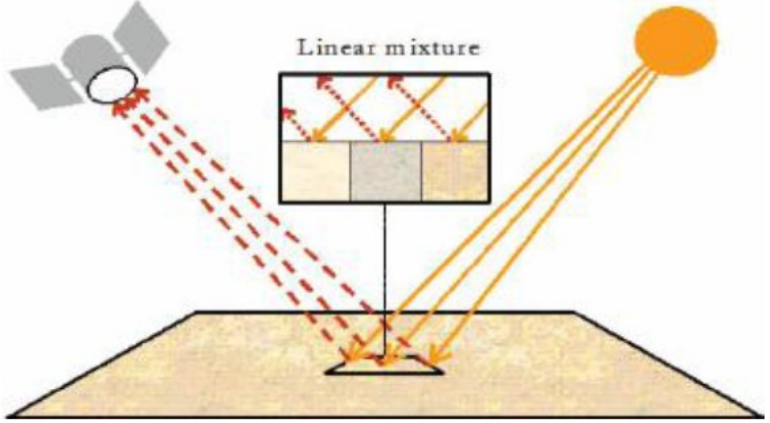
LINEAR

NON - LINEAR

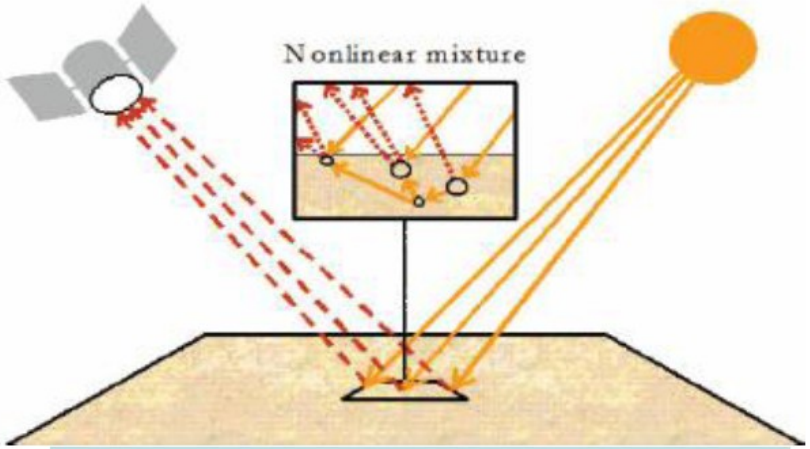
Depending on the mixing scales at each pixel, the observed mixture is either linear or nonlinear

A linear mixing model holds approximately when the mixing scale is macroscopic and there is negligible interaction among distinct endmembers

If the mixing scale is microscopic and the incident solar radiation is scattered by the scene through multiple bounces involving several endmembers, the linear model is no longer accurate



(a) The linear mixing model assumes a well-defined proportional checkerboard mixture of materials, with a single reflection of the illuminating solar radiation



(b) Nonlinear mixing models assume a randomly distributed, homogeneous mixture of materials, with multiple reflections of the illuminating radiation

FULL UNMIXING PARTIAL UNMIXING

Complete spectral ununixing of a hyper spectral scene may not always be possible or even desired

Spectrally complex & very high dimensional data are difficult to fully unravel

Partial unmixing provides a way of mapping endmembers of interest

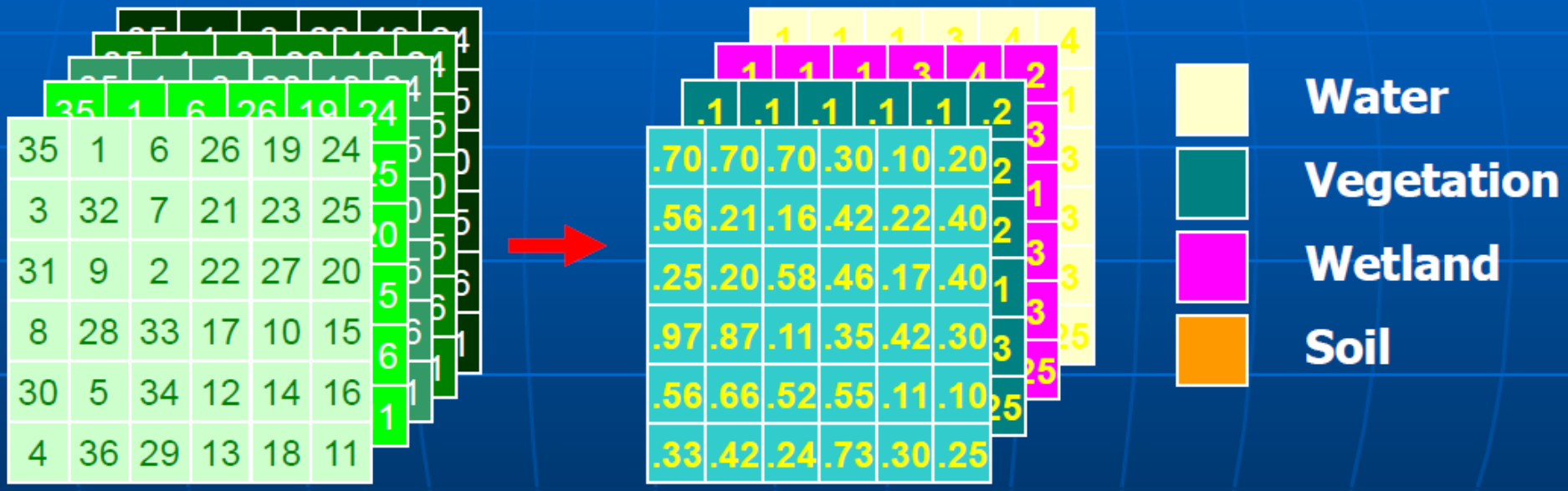
Many applications of imaging spectrometry can be cast in the form of the following question:

“Are my target signatures present in the scene, and if so, how much of each target material is present in each pixel?”

Number of unmixing endmembers is one greater than the number of spectrally defined target materials

One additional endmember can be thought of as the composite of all the other scene materials, or “everything else”

Sub-pixel Classification

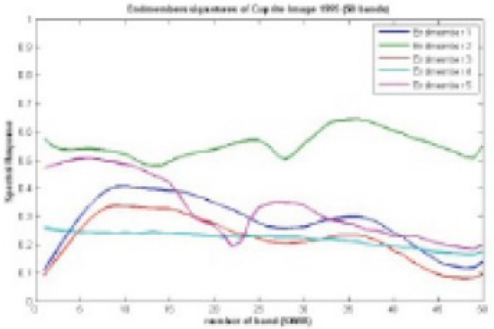


Remote Sensing image

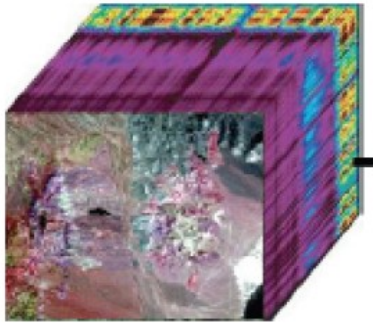
Fuzzy outputs

Conceptual diagram of end-to-end spectral Unmixing

Endmembers Signatures



Hyperspectral Cube



Cuprite, NV
50 bands

Dimensional reduction

Endmember determination

Inversion

Abundance Map

Linear - Constrained Unmixing

$$R = \sum_{i=1}^{N} f_i R_i$$

where,

R is the effective reflectance of the mixed pixel,

R_i is the reflectance of the i^{th} material (end member),

f_i is the spatial fraction covered by the i^{th} material and

N is the number of materials in the pixel

Linear - Constrained Unmixing

Given an M spectral band sensor with the bands designated with a j subscript, we can write M equations of the form

$$R_j = \sum_{i=1}^{N} f_i R_{ij} \quad \text{in reflectance space}$$

$$\text{or } L_j = \sum_{i=1}^{N} f_i L_{ij} \quad \text{in radiance space}$$

Linear -Constrained Unmixing

If we can claim to know the spectral reflectance or radiance for the materials potentially in each pixel (i.e., the endmember) we can write M simultaneous linear equations in N unknowns (i.e.,the fractions are the only unknowns).

In matrix/vector form, this looks like

$$\begin{bmatrix} L_1 \\ L_2 \\ \vdots \\ L_M \end{bmatrix} = \begin{bmatrix} L_{11} & L_{21} & \cdots & L_{N1} \\ L_{12} & L_{22} & \cdots & L_{N2} \\ \vdots & \vdots & \vdots & \vdots \\ L_{1M} & L_{2M} & \cdots & L_{NM} \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{bmatrix}$$

$$\vec{L} = [\vec{e}1 \quad \vec{e}3 \quad \ldots \quad \vec{e}_N]F$$

$$\vec{L} = E\vec{F}$$

Linear - Constrained Unmixing

Take a simple 3-band 3-end member case with end member reflectance vectors.

$$\vec{e}_{water} = \begin{bmatrix} 4 \\ 2 \\ 2 \end{bmatrix}, \vec{e}_{land} = \begin{bmatrix} 16 \\ 20 \\ 24 \end{bmatrix}, \vec{e}_{veg} = \begin{bmatrix} 4 \\ 8 \\ 4 \end{bmatrix} \text{ so } \mathbf{E} = \begin{bmatrix} 4 & 16 & 4 \\ 2 & 20 & 8 \\ 2 & 24 & 4 \end{bmatrix}$$

$$\vec{R} = \begin{bmatrix} 7 \\ 8 \\ 8 \end{bmatrix} \text{ yielding } \begin{aligned} 7 &= 4f_i + 16f_2 + 4f_3 \\ 8 &= 2f_i + 20f_2 + 8f_3 \\ 8 &= 2f_i + 24f_2 + 4f_3 \end{aligned}$$

For any Pixel

Linear - Constrained Unmixing

Solving for f1, f2, and f3 yields

$$\vec{F} = \begin{bmatrix} \mathbf{0.5} \\ \mathbf{0.25} \\ \mathbf{0.25} \end{bmatrix}$$

When we add error into the system, we must recognize that without constraining the system, a least squares solution may yield a best estimate for the fractions

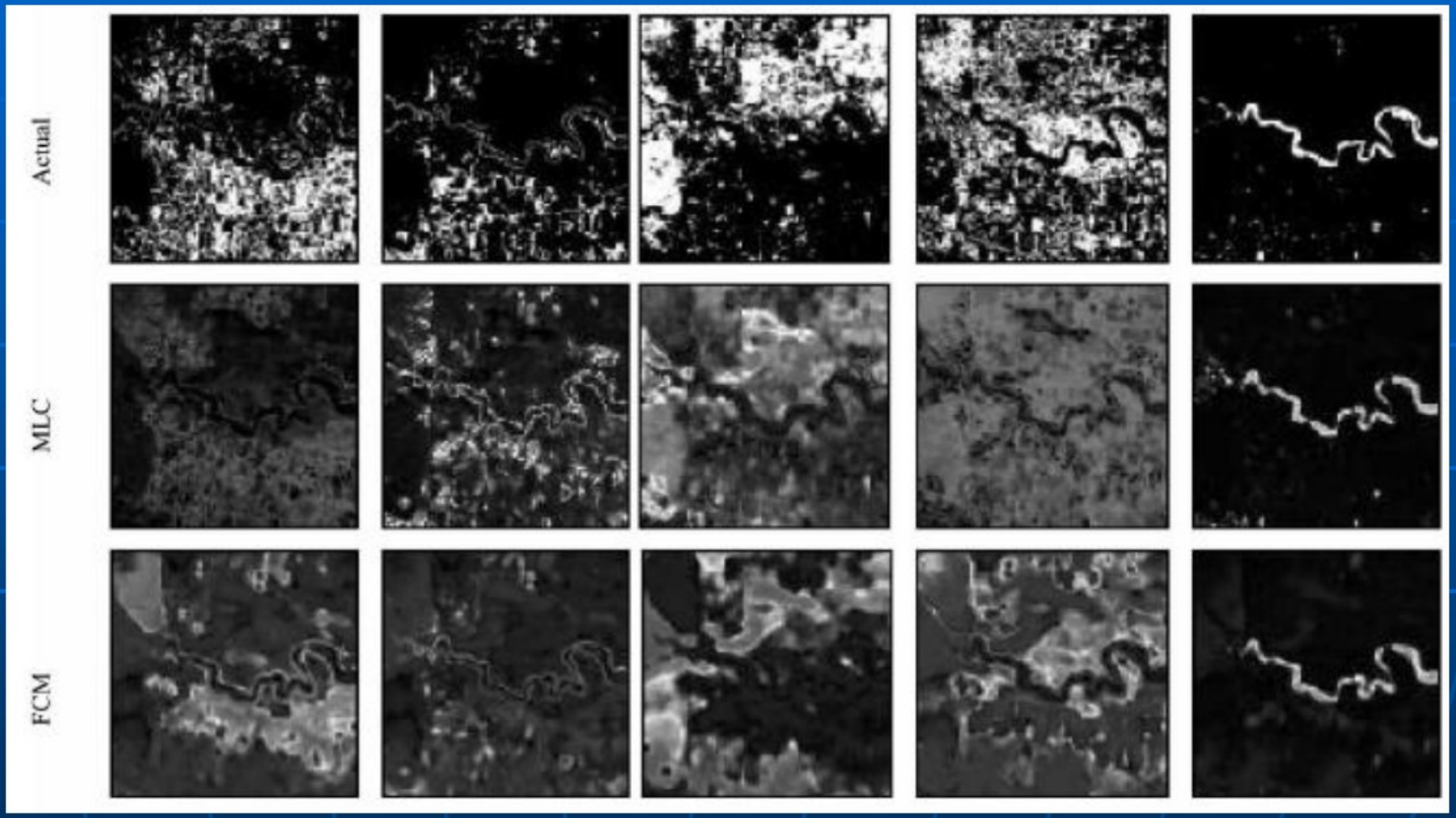
For avoiding instances like

Two very different types of unmixing are typically used: Using "known" endmembers and using "derived" endmembers.

Using known endmembers, one seeks to derive the apparent fractional abundance of each endmember material in each pixel, given a set of "known" or assumed spectral ndmembers.

These known endmembers can be drawn from the data (averages of regions picked using previous knowledge), drawn from a library of pure materials by interactively browsing through the imaging spectrometer data to determine what pure materials exist in the image

Fraction Images



Agriculture Urban Forest Grass Sand

Matched filtering

The technique is a unique approach to spectral mixture modelling

in that it does not require knowledge of the spectral signatures of other component materials (Boardman 1998). A type of unmixing in which only user chosen targets are mapped

Unlike Complete Unmixing, to find the spectra of all endmembers in the scene to get an accurate analysis (hence, this type of analysis is often called a "partial unmixing" because the unmixing equations are only partially solved)

Matched Filtering "filters" the input image for good matches to the chosen target spectrum by maximizing the response of the target spectrum within the data and suppressing the response of everything else (which is treated as a composite unknown background to the target)

Pixel value in the output image is proportional to the fraction of the pixel that contains the target material

Matched filtering

MF vector equates to target abundance estimations that range from 0 to 100% (Mundt et al. 2007). Spectra that closely match the training spectrum will have a score near one while background noise will have a score near zero. Any pixel with a value of 0 or less would be interpreted as background (i.e., none of the target is present).

One potential problem with Matched Filtering is that it is possible to end up with false positive results

One solution to this problem that is available in ENVI is to calculate an additional measure called “infeasibility”. Which is the method called MTMF

Is a hybrid method based on the combination of the matched filter method (no requirement to know all the endmembers) and linear mixture theory

Mixture Tuned Matched Filtering (MTMF)

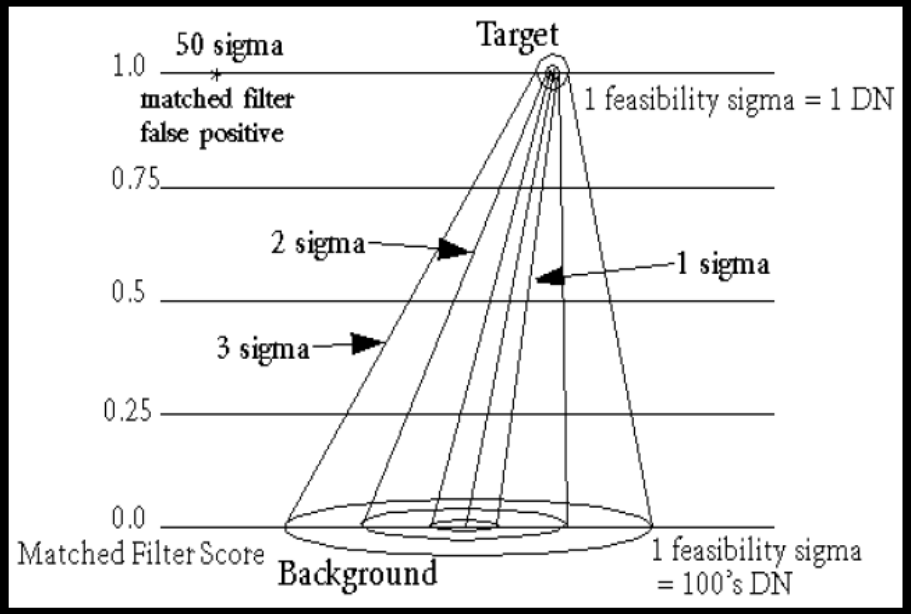
The results are two images:

- ✓ **MF score image with 0 to 1 (perfect match), and**
- ✓ **Infeasibility image, the smaller the better match**

- ❖ **Infeasibility is based on both noise and image statistics and indicates the degree to which the Matched Filtering result is a feasible mixture of the target and the background**

- ❖ **Pixels with high infeasibilities are likely to be false positives regardless of their matched filter value**

- ❖ **Use 2-D scatter plot to locate those pixels in image**



This technique may find some "false positives" that shows high values in terms of matching score for rare materials which is taken care of by an output "infeasibility" image to the results.

The infeasibility image is used to reduce the number of "false positives" that are sometimes found using matched filtering technique. Pixels with a high infeasibility are likely to be matched filter false positives. Correctly mapped pixels will have a high matched filter score and a low infeasibility value where as Pixels with a high matched filter result and high infeasibility are "false positive" pixels and do not match the target. The infeasibility values are in noise sigma units which vary in digital number scale with matched filter score and indicate the feasibility of the matched filter results (Harsanyi & Chang, 1994; Chen & Reed, 1987).

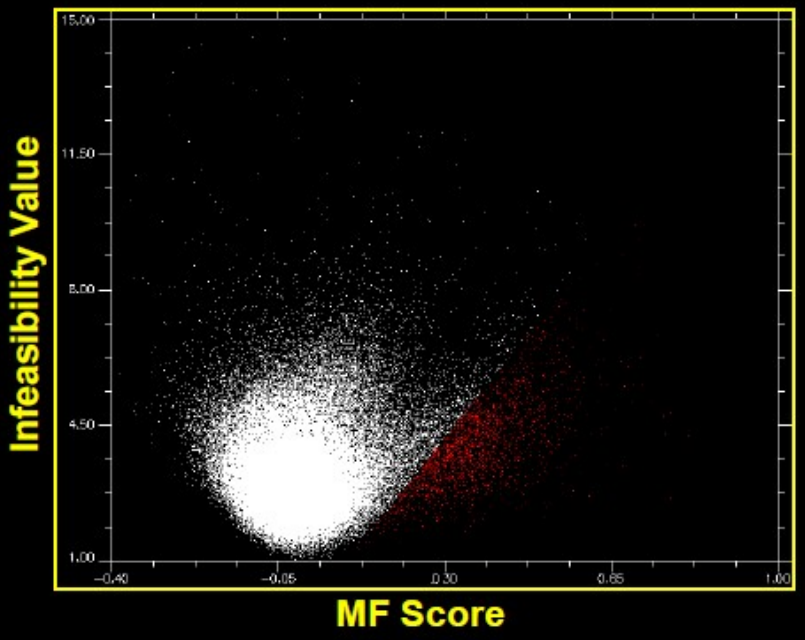
Mixture Tuned Matched Filtering technique combines the best part of the linear spectral unmixing model and the statistical matched filter model while avoiding the drawbacks of each model. From matched filtering it inherits the advantage of its ability to map a single known target without knowing the other background endmember signatures, unlike traditional spectral mixing models.

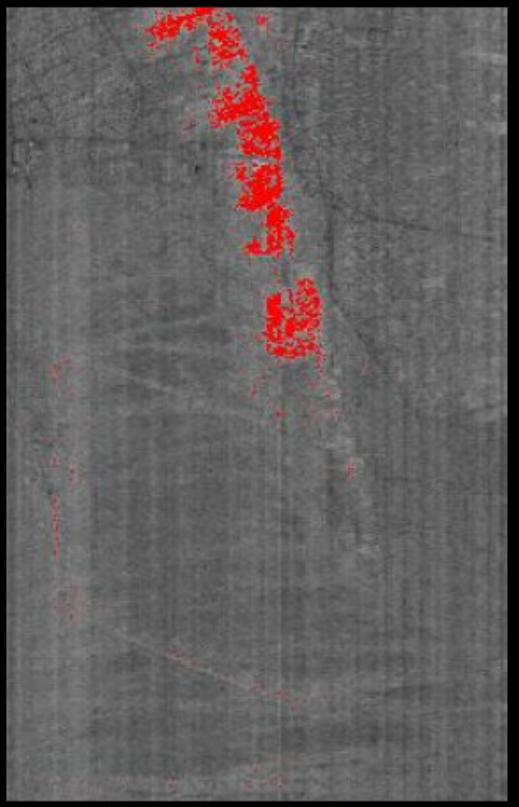
MTMF (Mixture-Tuned Matched Filtering)

- Is a hybrid method based on the combination of the matched filter method (no requirement to know all the endmembers) and linear mixture theory.
- The results are two images:
  - a MF score image with 0 to 1 (1 is perfect match), and
  - A infeasibility image, the smaller the better match.
    - Infeasibility is based on both noise and image statistics and indicates the degree to which the Matched Filtering result is a feasible mixture of the target and the background. Pixels with high infeasibilities are likely to be false positives regardless of their matched filter value.
  - Use 2-D scatter plot to locate those pixels in an image.

Mixture Tuned Matched Filtering (MTMF)

FCC





MF Score image

Sandstone

Spectral Derivative Analysis

Benefited from the high spectral resolution of hyperspectral data, the reflectance could construct a comparatively continuous curve, and thus the derivative method is likely to be used for data analysis.

From one hand, the derivative processing could enhance the small variations of spectral curve (Li, 2006). And from the other hand, the derivatives could also be relatively less sensitive to the spectral variations of sunlight and skylight (Tsai and Philpot, 1998), and also eliminate background signals (Becker et al, 2005).

The First Derivative Reflectance (FDR) and Second Derivative Reflectance (SDR) were calculated according to Eq. (1) and Eq. (2). For FDR method,

$$FDR_{\lambda_i} = \frac{dR}{d\lambda} = \frac{R_{\lambda_{j+1}} - R_{\lambda_j}}{\Delta\lambda} \quad (1)$$

$$SDR_{\lambda_i} = \frac{d^2R}{d\lambda^2} = \frac{d}{d\lambda}\left(\frac{dR}{d\lambda}\right) = \frac{R_{\lambda_{j+2}} - 2R_{\lambda_{j+1}} + R_{\lambda_j}}{(\Delta\lambda)^2} \quad (2)$$

Where

$FDR_{\lambda i}$	=	The FDR between band j and band j+1, where wavelength equals to *i*;
$SDR_{\lambda i}$	=	The SDR between band j and band j+2, where wavelength equals to *i*;
$R_{\lambda j}$, $R_{\lambda j+1}$, $R_{\lambda j+2}$	=	Reflectance of band j, j+1, j+2;
$\Delta\lambda$	=	Difference of wavelength between band j and band j+1.

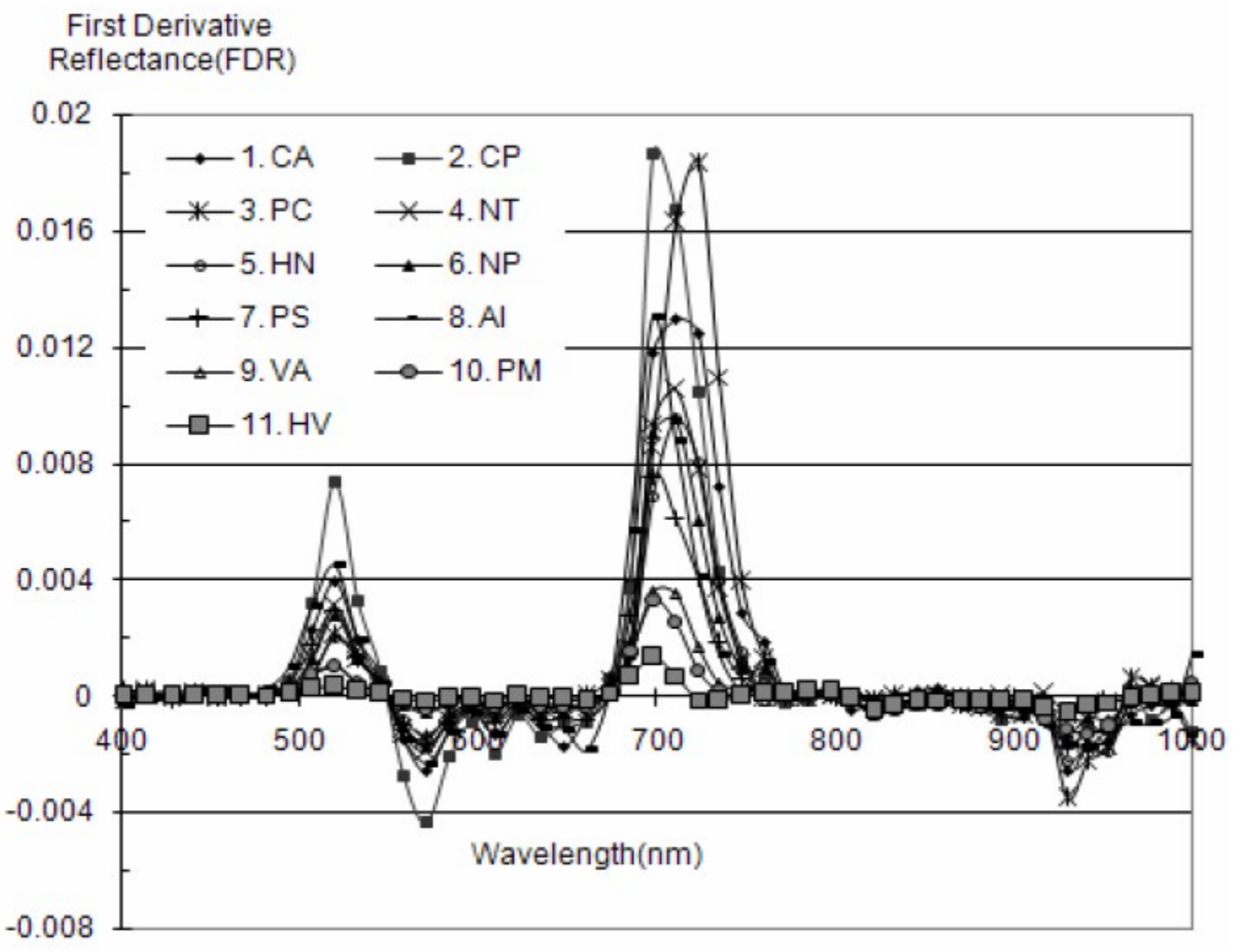


Figure 4. Comparison of the FDR curves for 11 wetland species.

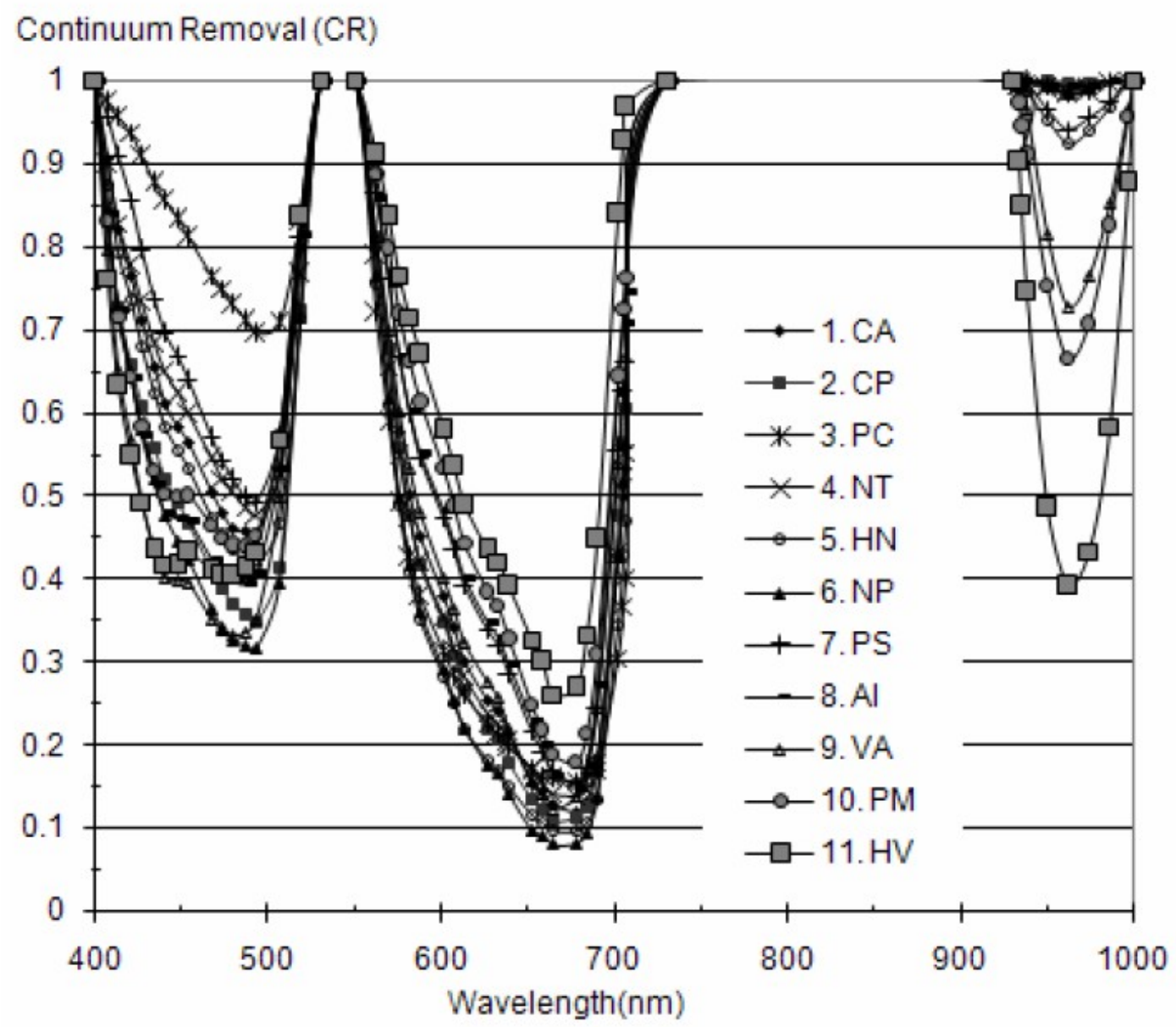


Figure 6. Comparison of the CR curves for 11 wetland species.

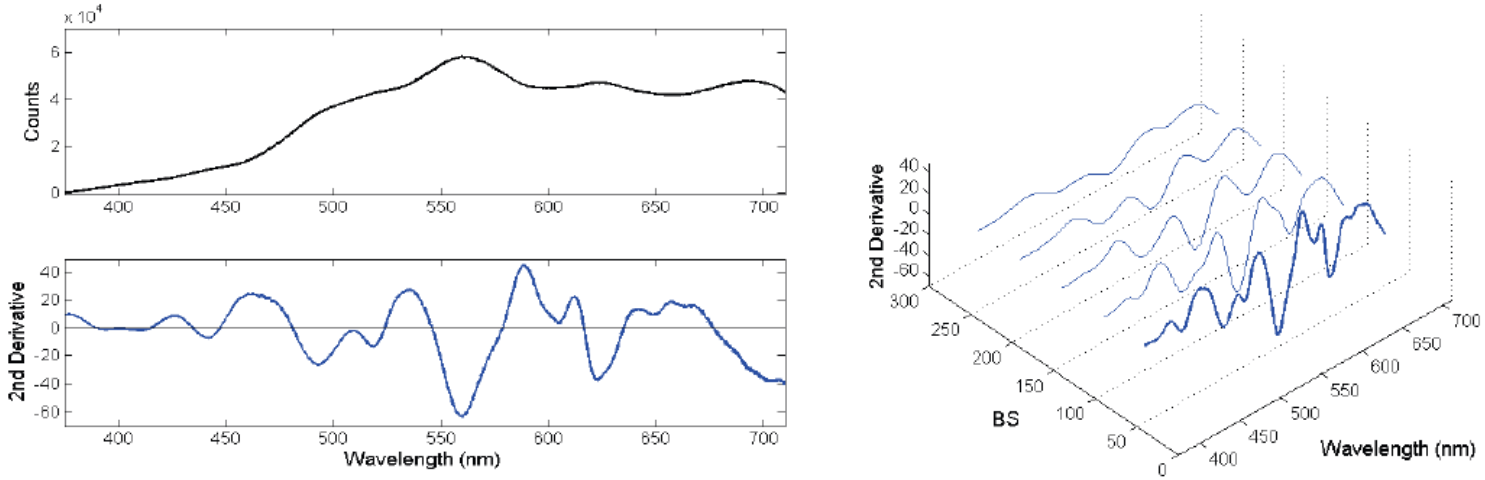


Fig. 6. (Left) Original spectrum and its second derivative of a water sample containing a unique phytoplankton algal culture (*Alexandrium minutum*), acquired by a miniature hyperspectral CCD-array spectrometer. (Right) Second derivatives computed for several values of band separation (BS), each of them leading to spectral features at different scales.

Spectral parameters

- **Radius of curvature**
  - Radius of curvature of NIR absorption trough
  - Radius of curvature of Al absorption trough
- **Slope**
  - Slope (685-725nm)
  - Slope (850-1000nm)
- **FWHM**
- **Distance from the reference line**
  - Distance to NIR absorption trough
  - Distance to Al absorption trough
- **Area Under Curve**
  - AUC(350-2500nm)
  - AUC(750-1000 nm)
  - AUC(2130-2230nm)
- **Area Above Curve**
  - AAC (Area Above Curve)-NIR
  - AAC (Area Above Curve)-(2130-2230nm)
- **Position of Peak/Trough**
  - Position-NIR absorption trough
  - Position-VNIR reflectance peak
  - Position-Al absorption trough
- **Distance/Strength of absorption**
  - Distance to NIR absorption trough
  - Distance-Al-Trough (2130-2230nm)
- **Derivative spectra**
- **Spectral indices**

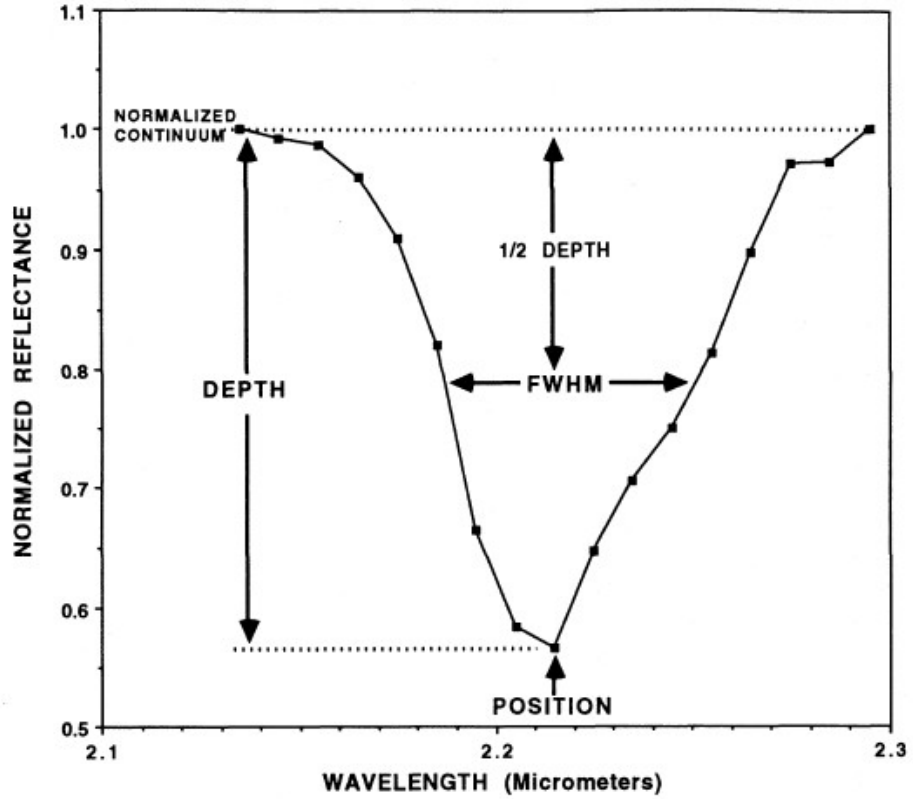


FIGURE 4 Plot showing the absorption band attributes position, depth, and full-width-half-max (FWHM).

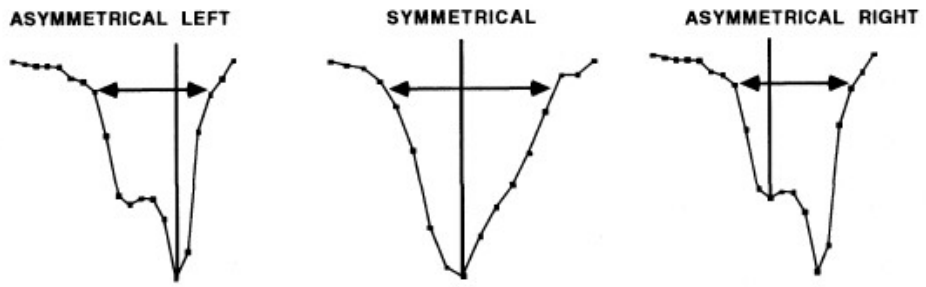


FIGURE 5 Schematic showing the absorption band attribute asymmetry. Note the distribution of the areas to the left and right of the selected absorption minimum.