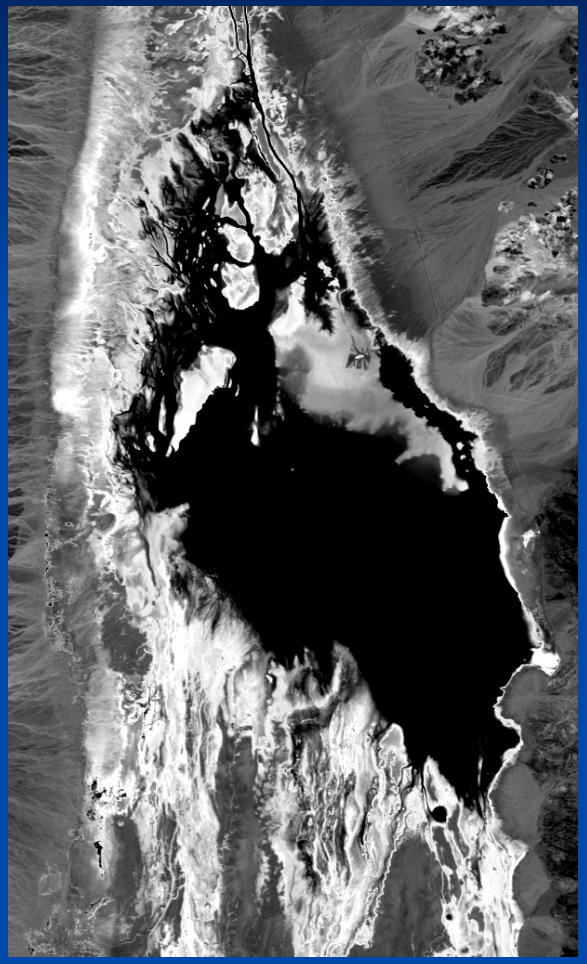
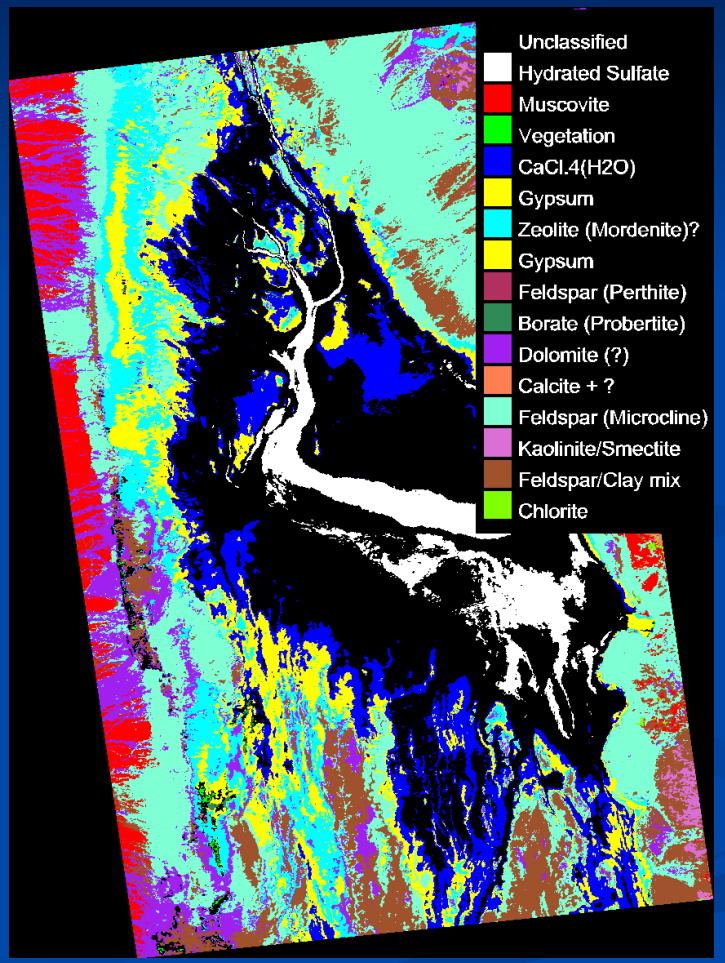
“Continuous” vs. “Discrete” Spectral Mapping

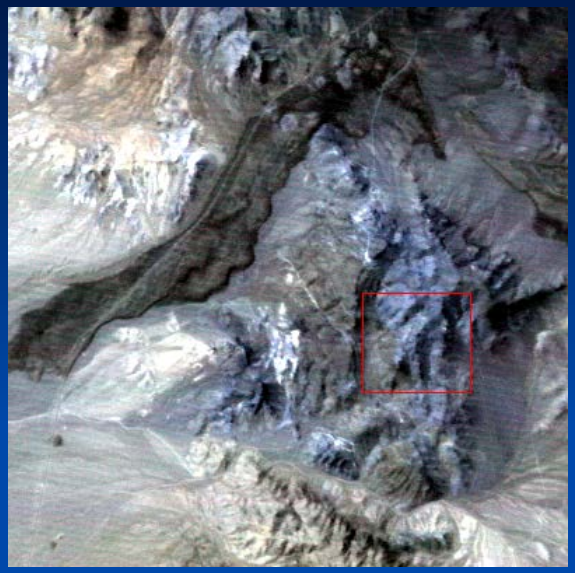


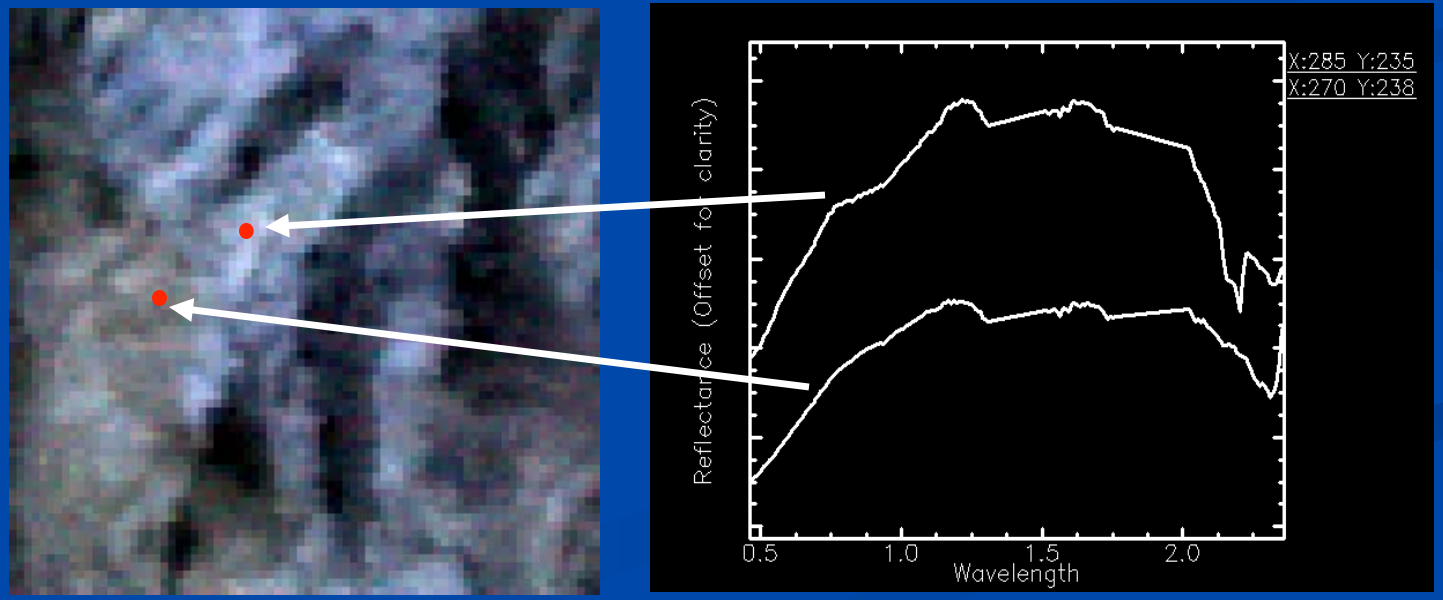
Map that highlights a particular composition



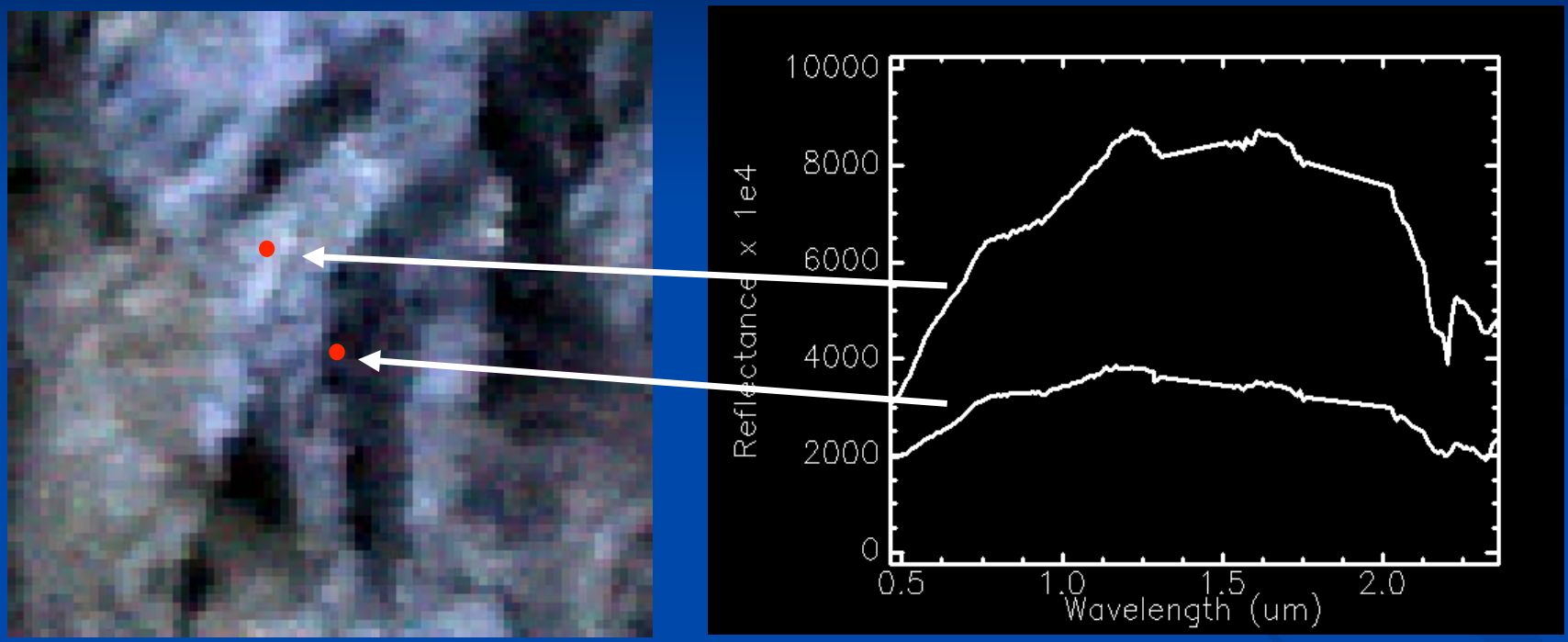
Map that attempts to classify every pixel in the scene

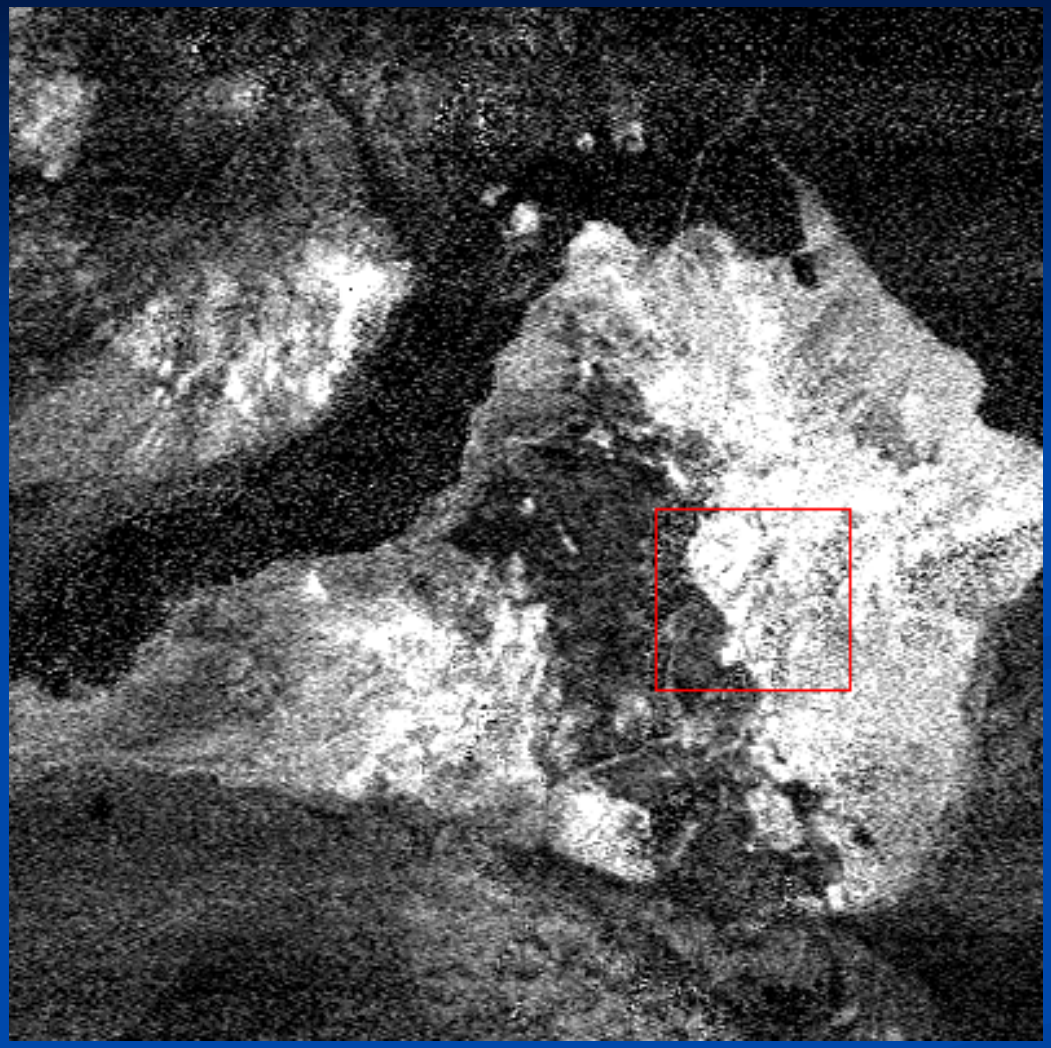
Band Ratios and Color



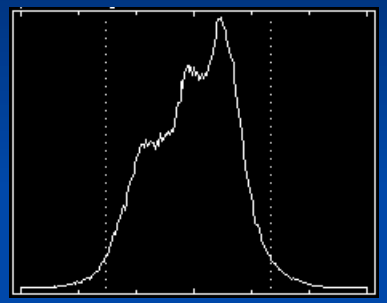


Same composition, different illumination

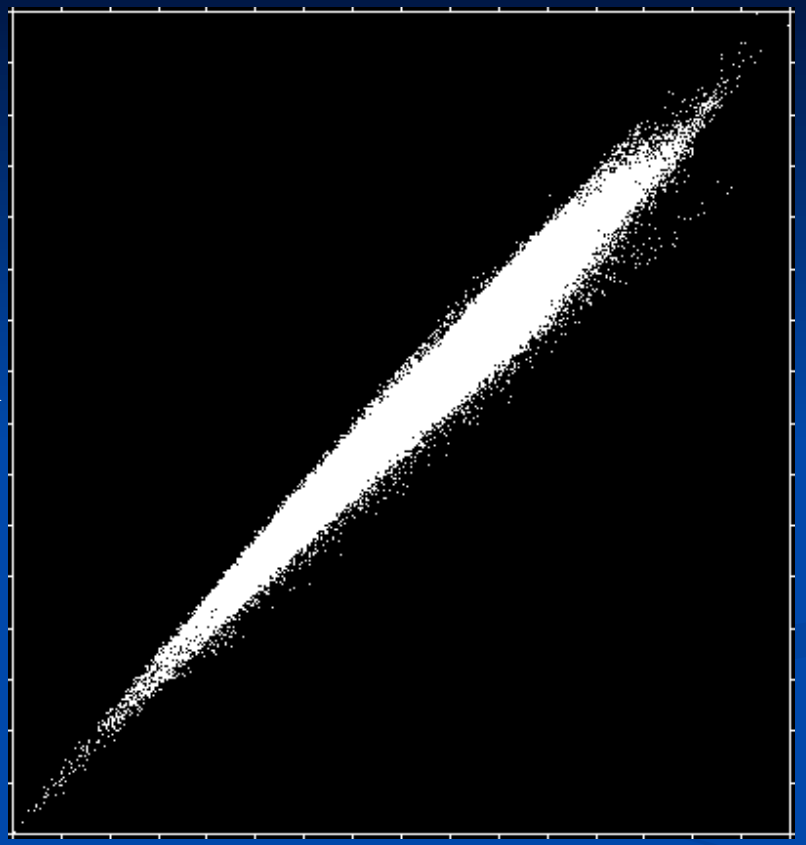




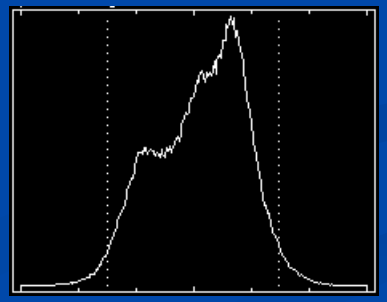
Band Ratio 2.10μm / 2.22 μm



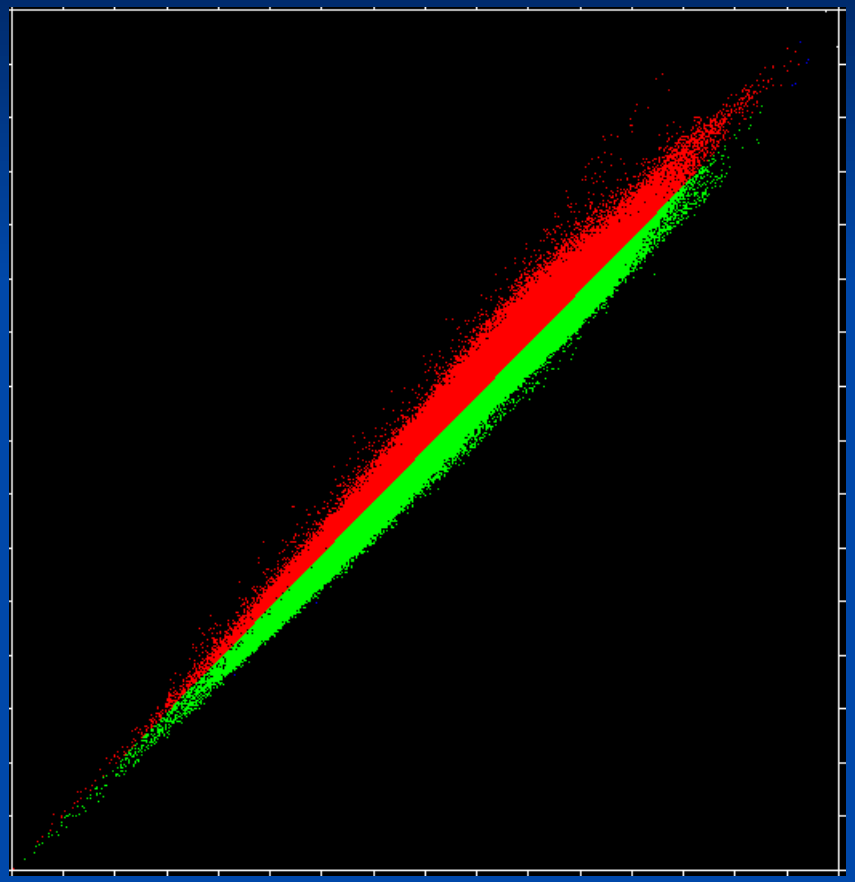
2.10 μm



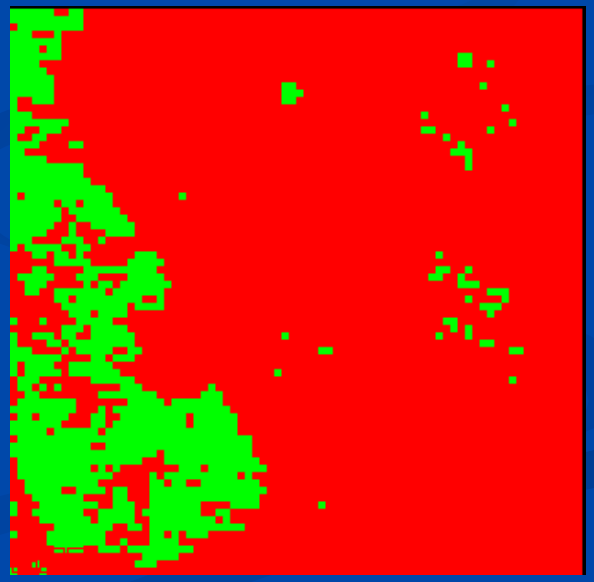
2.22 μm



2.10 μm



2.22 μm



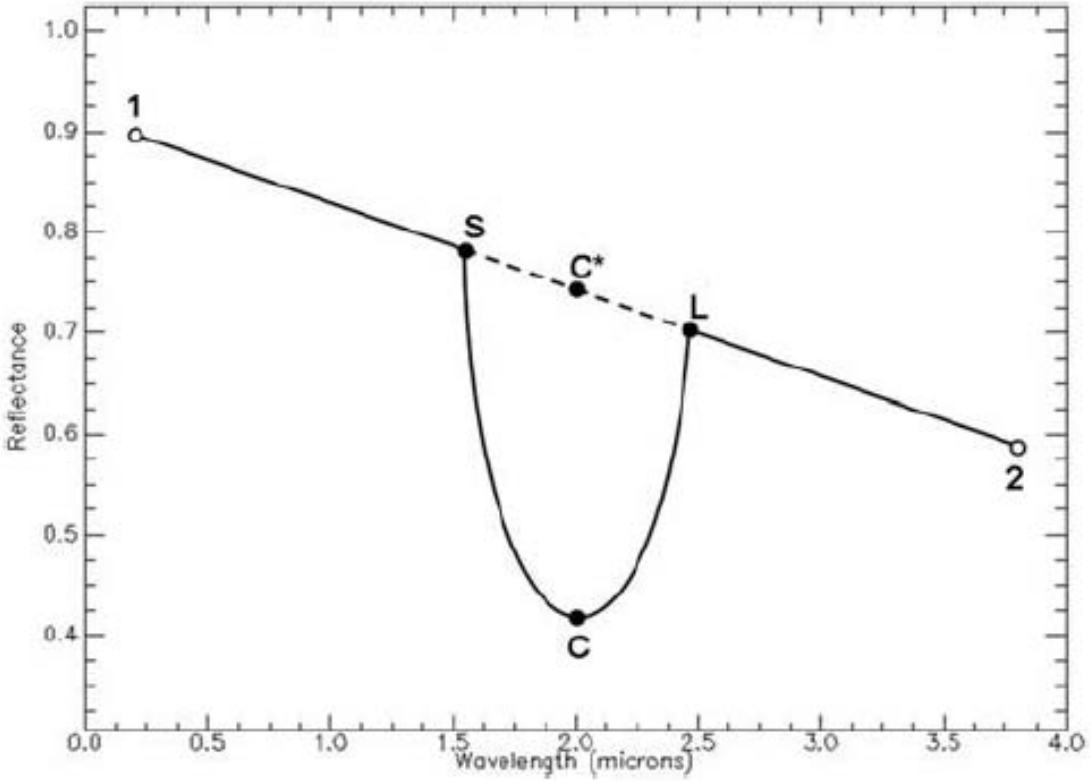


Figure 1. An explanation of some of the most common spectral parameters using an idealized spectrum. The solid line is an idealized spectrum with an absorption band superimposed on a sloped continuum. In the above example, the reflectance at the wavelength indicated by the point labeled 1 (i.e., at λ_1) is represented as R_1. Spectral slope is found by $(R_1 - R_2)/(\lambda_1 - \lambda_2)$. Band depth is found by $1 - R_C/R_{C*}$, where the point labeled C indicates the center of the absorption at λ_C, R_C is the reflectance at that wavelength, and R_{C*} is derived from the continuum fit along the dashed line and is equal to $(a*R_S + b*R_L)$, where $a = 1\text{-}b$ and $b = (\lambda_C - \lambda_S)/(\lambda_L - \lambda_S)$.

Can go beyond simple band ratios to band depths…

Pelkey et al. (2007)

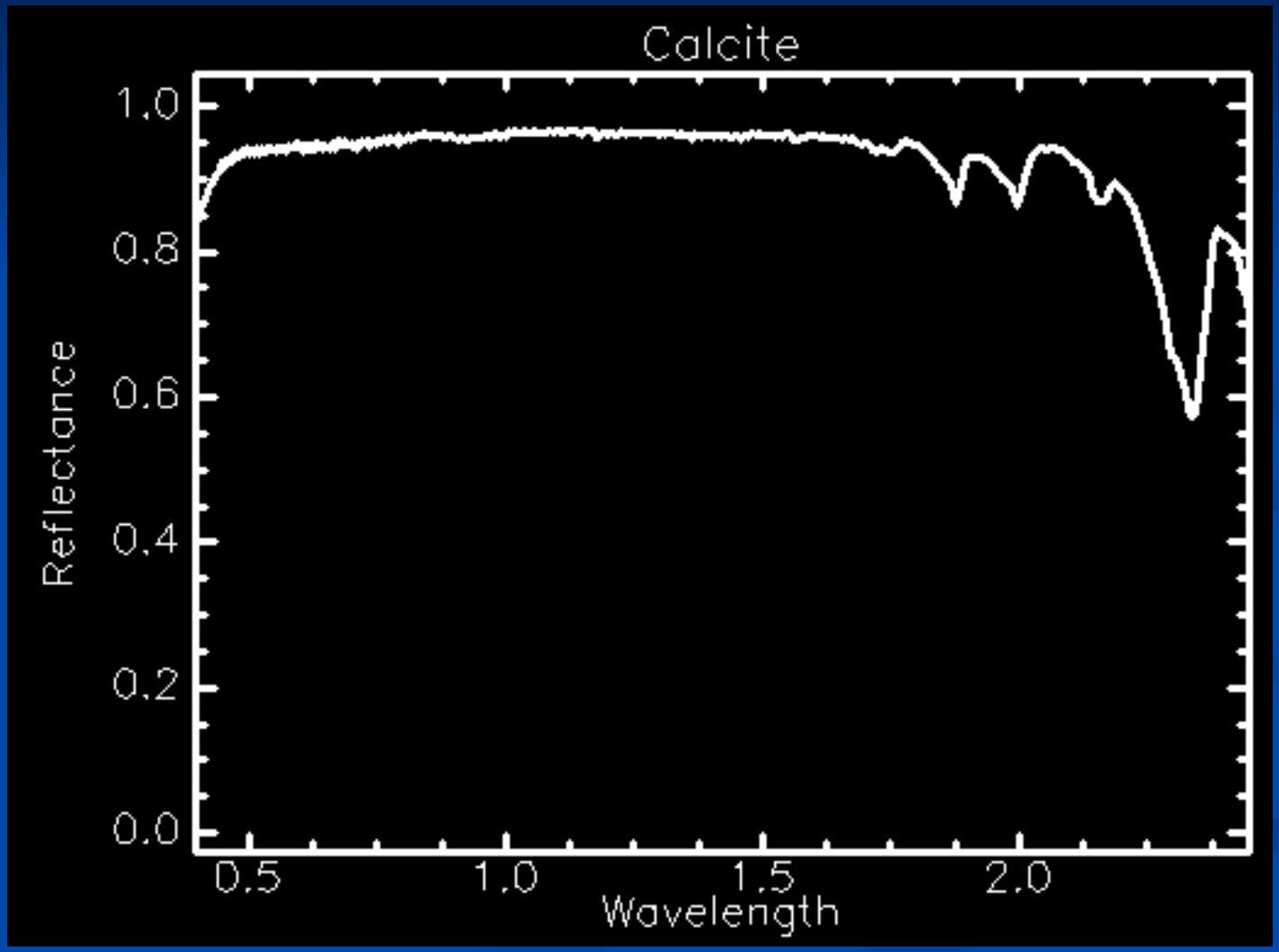
Table 1. CRISM Spectral Parameter Summary Products[a]

Name	Parameter	Formulation[b]	Rationale
		Surface Parameters [c]	
R770	0.77 μm reflectance	R770	rock/dust
RBR	red/blue ratio	R770/R440	rock/dust
BD530	0.53 μm band depth	1 − (R530/(a*R648 + b*R440))	crystalline ferric minerals
SH600	0.60 μm shoulder height	R600/(a*R530 + b*R680)	select ferric minerals
BD640	0.64 μm band depth	1 − (R648/(a*R600 + b*R680))	select ferric minerals
BD860	0.86 μm band depth	1 − (R860/(a*R800 + b*R920))	select ferric minerals
RPEAK1	reflectance peak 1	wavelength where 1st derivative = 0 of 5th order polynomial fit to R600, R648, R680, R710, R740, R770, R800, R830	Fe mineralogy
BDI1000VIS	1 μm integrated band depth; VIS wavelengths	divide R830, R860, R890, R920 by RPEAK1 then integrate over (1 − normalized reflectances)	Fe mineralogy
BDI1000IR	1 μm integrated band depth; IR wavelengths	divide R950, R980, R1020, R1050, R1080, R1150 by linear fit from peak R between 1.3–1.87 μm to R2530 extrapolated backward to remove continuum, then integrate over (1 − continuum-corrected reflectances)	Fe mineralogy
IRA	1.3 μm reflectance	R1330	IR albedo
OLINDEX	Olivine index	(R1695/(0.1*R1050 + 0.1*R1210 + 0.4*R1330 + 0.4*R1470)) − 1	olivine will be strongly positive; based on fayalite
LCPINDEX	pyroxene index	((R1330-R1050)/(R1330 + R1050)) * ((R1330-R1815)/(R1330 + R1815)	pyroxene will be strongly positive; favors LCP
HCPXINDEX	pyroxene index	((R1470-R1050)/(R1470 + R1050)) * ((R1470-R2067)/(R1470 + R2067)	pyroxene will be strongly positive; favors HCP
VAR	spectral variance	variance of observed data from a line fit from 1.0–2.3 μm	olivine and pyroxene will have high values
ISLOPE1	−1 * spectral slope1	(R1815-R2530)/(2530-1815)	ferric coating on dark rock
BD1435	1.435 μm band depth	1 − (R1430/(a*R1370 + b*R1470))	CO_2 ice
BD1500	1.5 μm band depth	1 − (R1510/(a*R1330 + b*R1695))	H_2O ice
ICER1	1.5 μm and 1.43 μm band ratio	R1510/R1430	CO_2, H_2O ice mixtures
BD1750	1.75 μm band depth	1 − (R1750/(a*R1660 + b*R1815))	gypsum
BD1900	1.9 μm band depth	1 − (((R1930 + R1985)*0.5)/(a*R1857 + b*R2067))	H_2O
BDI2000	2 μm integrated band depth	divide R1660, R1815, R2140, R2210, R2250, R2290, R2330, R2350, R2390, R2430, R2460 by linear fit from peak R between 1.3–1.87 μm to R2530, to remove continuum, then integrate over (1 − continuum-corrected reflectances)	Fe mineralogy
BD2100	2.1 μm band depth	1 − (((R2120 + R2140)*0.5)/(a*R1930 + b*R2250))	Monohydrated minerals
BD2210	2.21 μm band depth	1 − (R2210/(a*R2140 + b*R2250))	Al-OH minerals
BD2290	2.29 μm band depth	1 − (R2290/(a*R2250 + b*R2350))	Mg,Fe-OH minerals (@ 2.3); ALSO CO_2 ice (@ 2.292)
D2300	2.3 μm drop	1 − ((CR2290 + CR2320 + CR2330)/ (CR2140 + CR2170 + CR2210)) (CR values are observed R values divided by values fit along the slope as determined between 1.8–2.53 μm (essentially continuum corrected))	hydrated min; particularly phyllosilicates
D2400	2.4 μm drop	1 − ((CR2390 + CR2430)/ (CR2290 + CR2320)) (CR values are observed R values divided by values fit along the slope as determined between 1.8–2.53 μm (essentially continuum corrected))	hydrated min; particularly sulfates
ICER2	gauge 2.7 μm band	R2530/R2600	CO_2 ice will be $\gg$ 1; H_2O ice and soil will be ~1
BDCARB	2.33 & 2.53 μm band depth	1 − (sqrt [(R2330/(a*R2230 + b*R2390)) *(R2530/(c*R2390 + d*R2600))])	carbonate overtones
BD3000	3 μm band depth	1 − (R3000/(R2530*(R2530/R2210)))	H_2O
BD3100	3.1 μm band depth	1 − (R3120/(a*R3000 + b*R3250))	H_2O ice
BD3200	3.2 μm band depth	1 − (R3320/(a*R3250 + b*R3390))	CO_2 ice
BD3400	3.4 μm band depth	1 − ((a*R3390 + b*R3500)/(c*R3250 + d*R3630))	carbonates; organics
CINDEX	gauge 3.9 μm band	(R3750 + (R3750-R3630)/(3750-3630) * (3950-3750))/R3950 − 1	carbonates

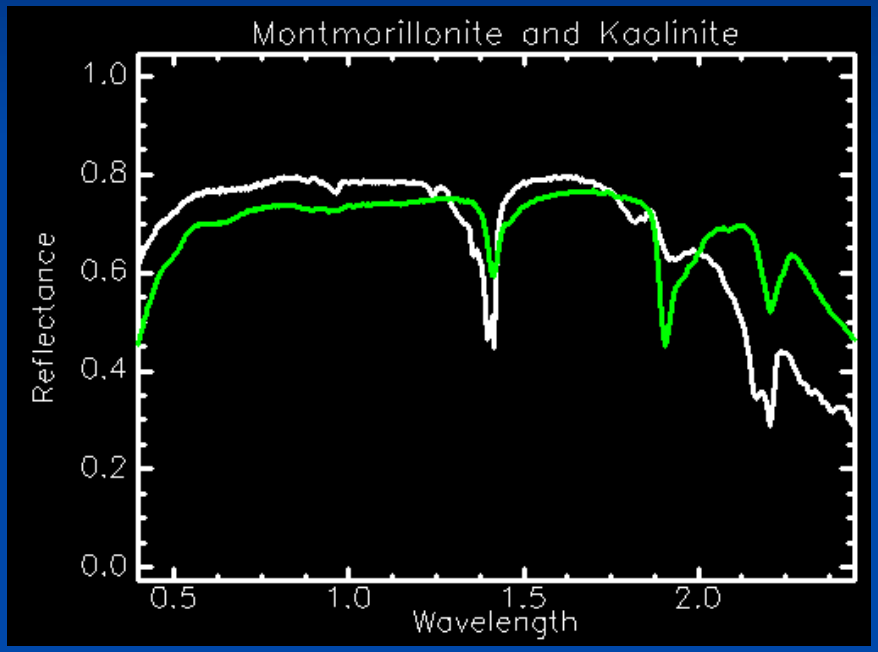
…or even more complex band math

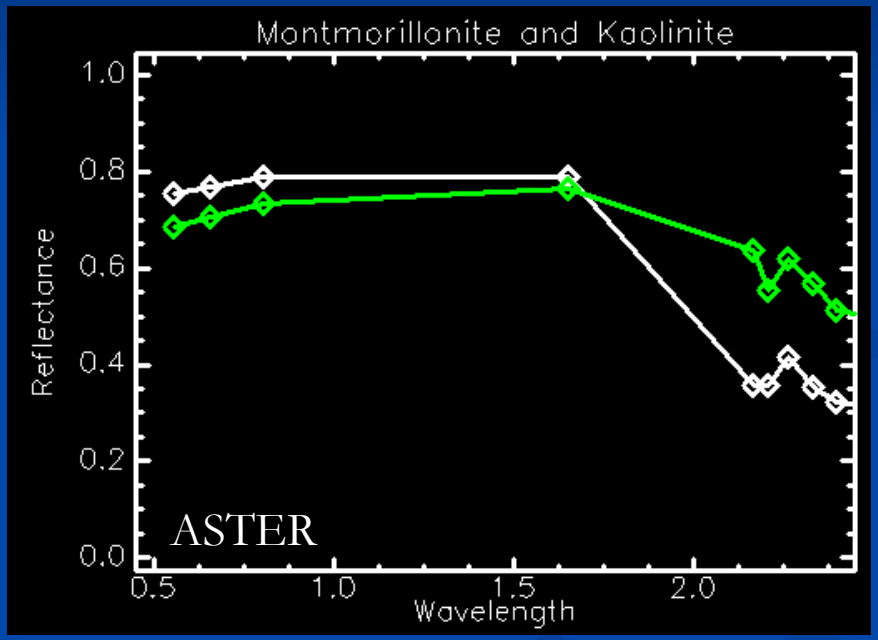
Pelkey et al. (2007)

Which bands would you ratio?

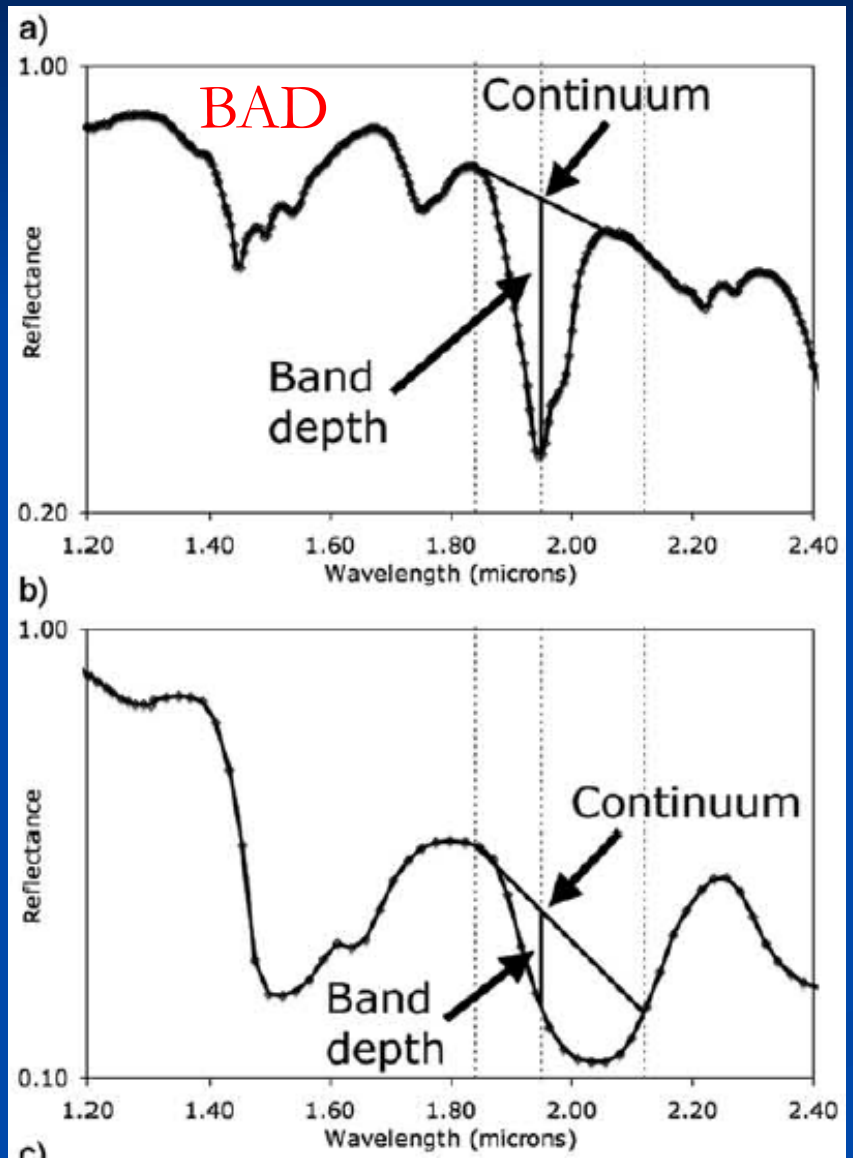


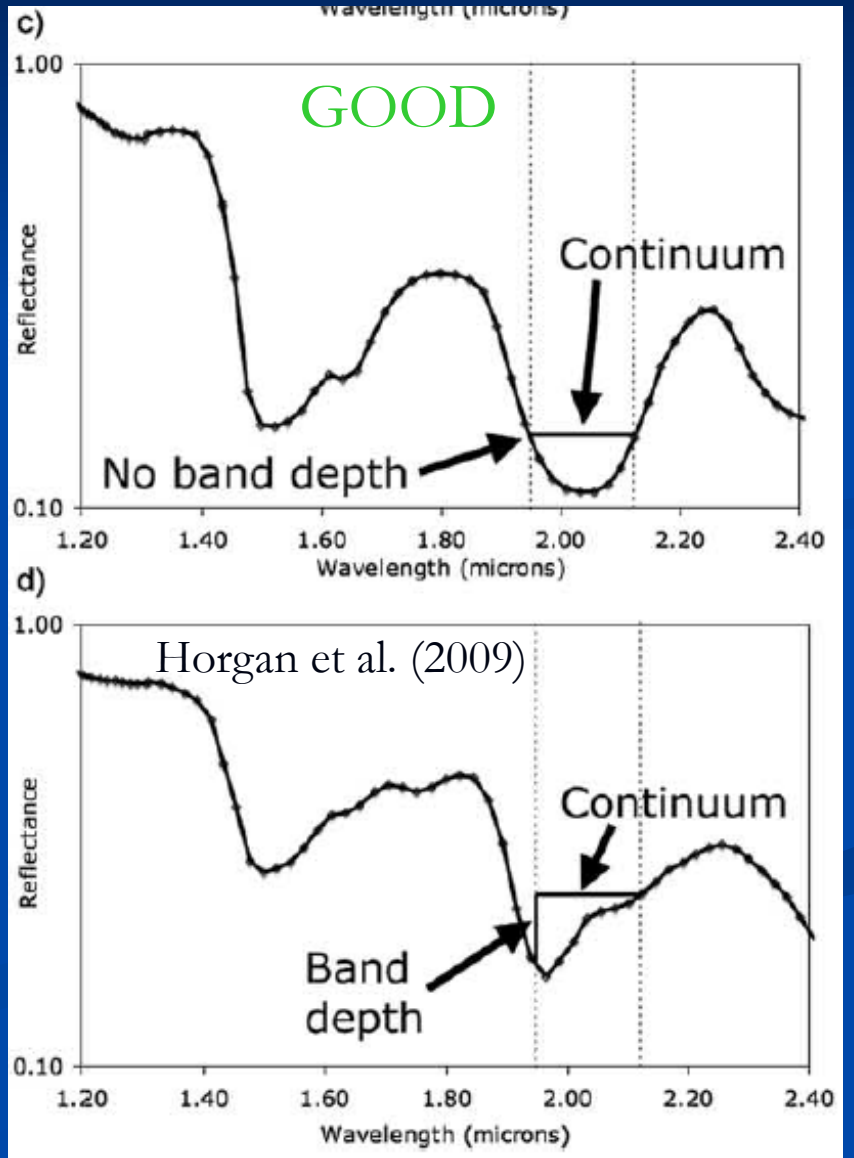
Which bands would you ratio?



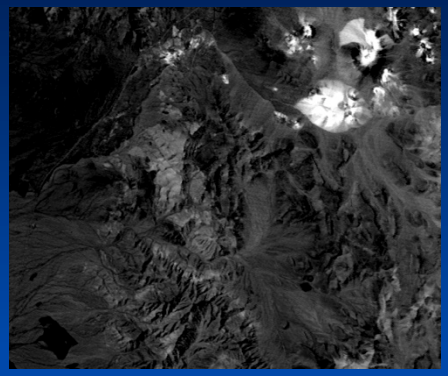


Distinguishing H_2O ice from hydrous minerals

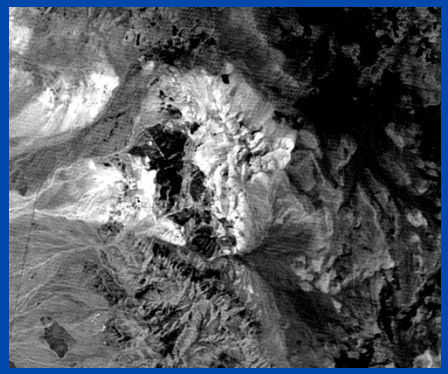




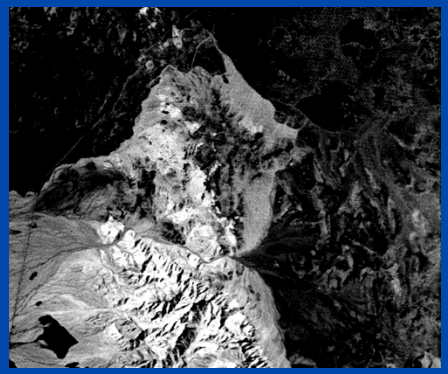
Color Composites from Continuous Images



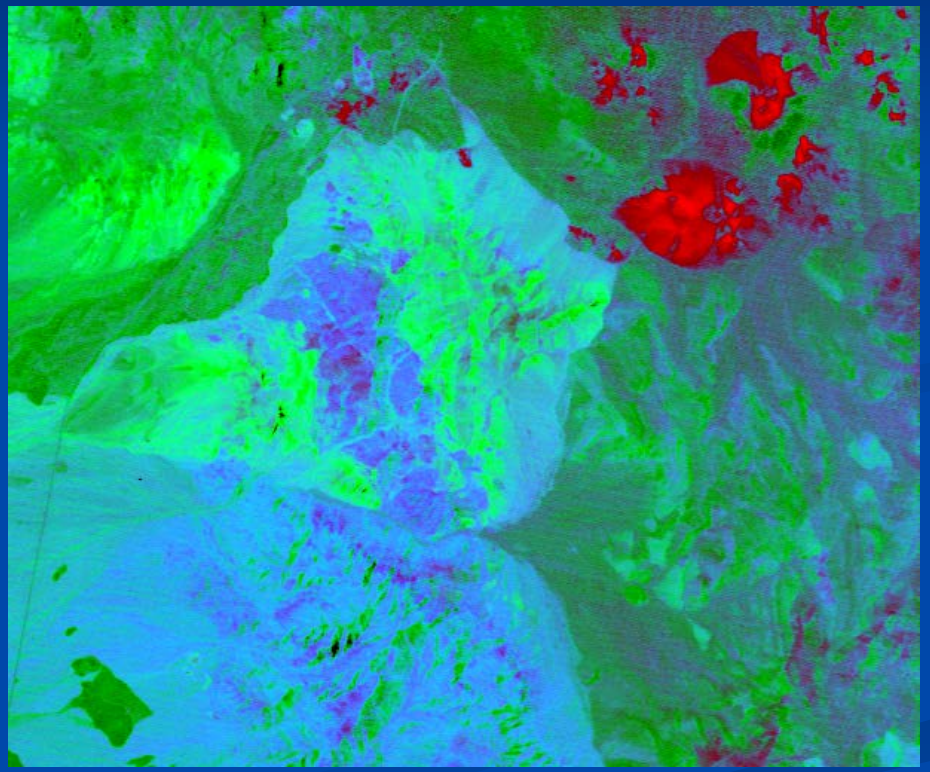
Hematite



Kaolinite

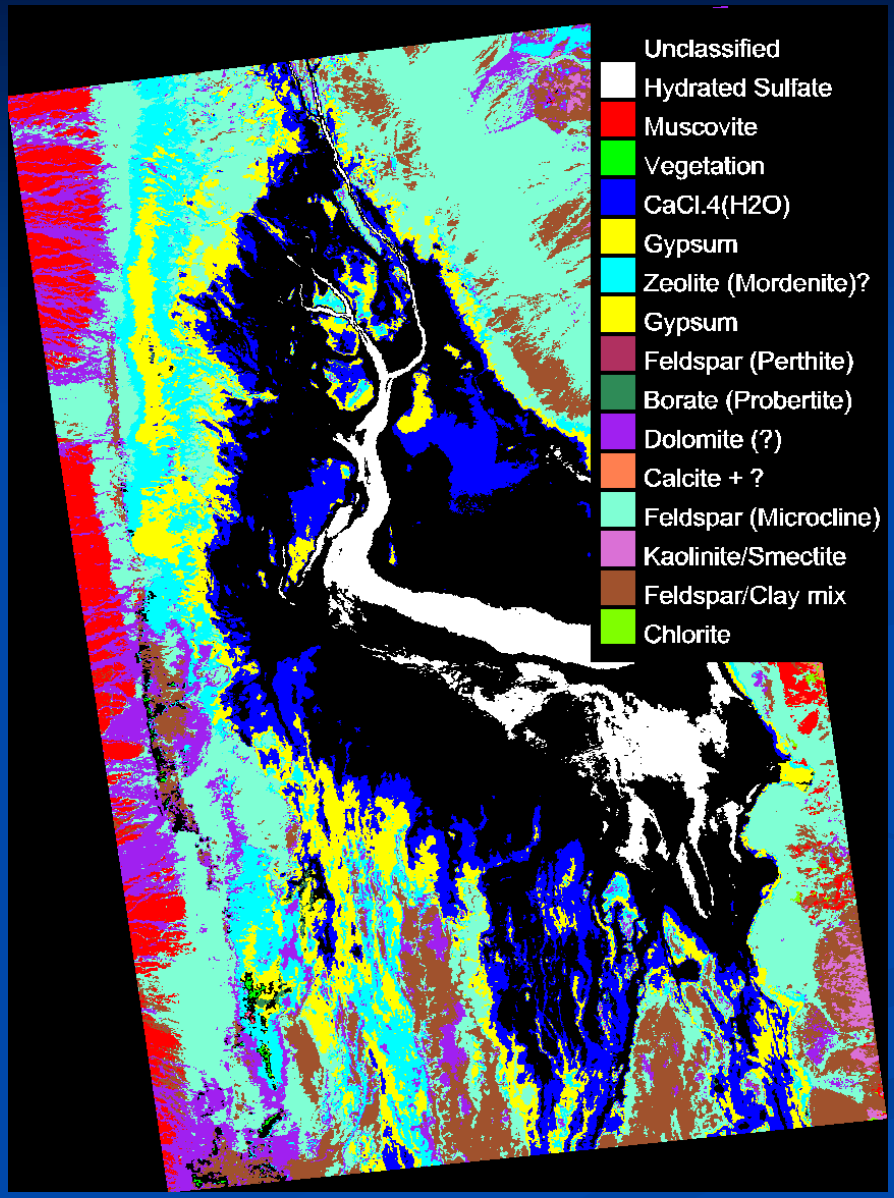


Dolomite

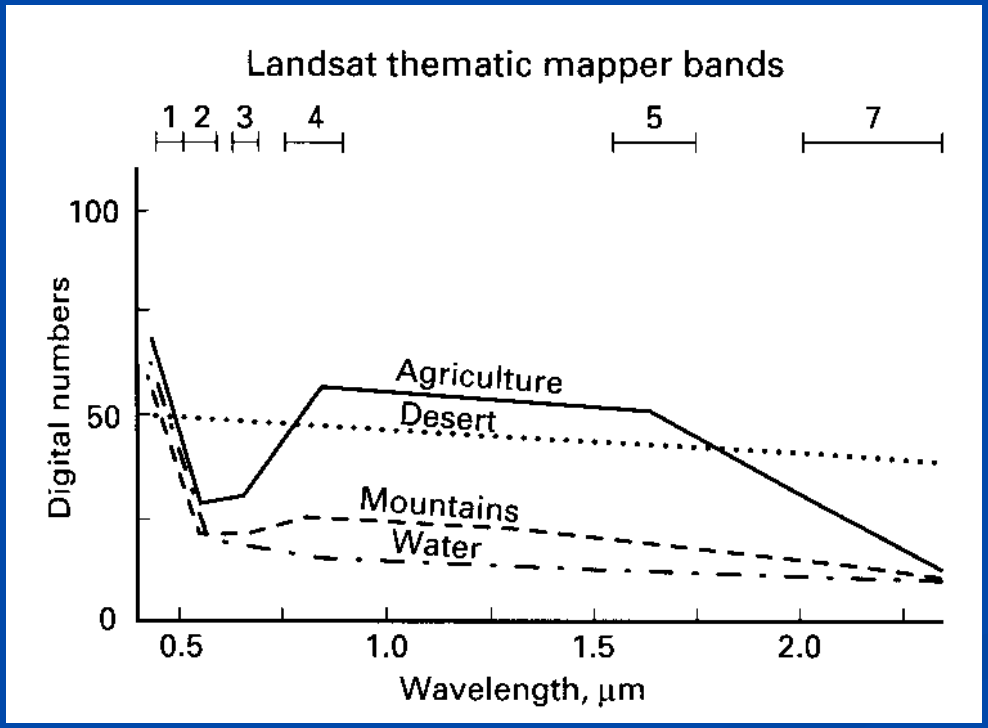


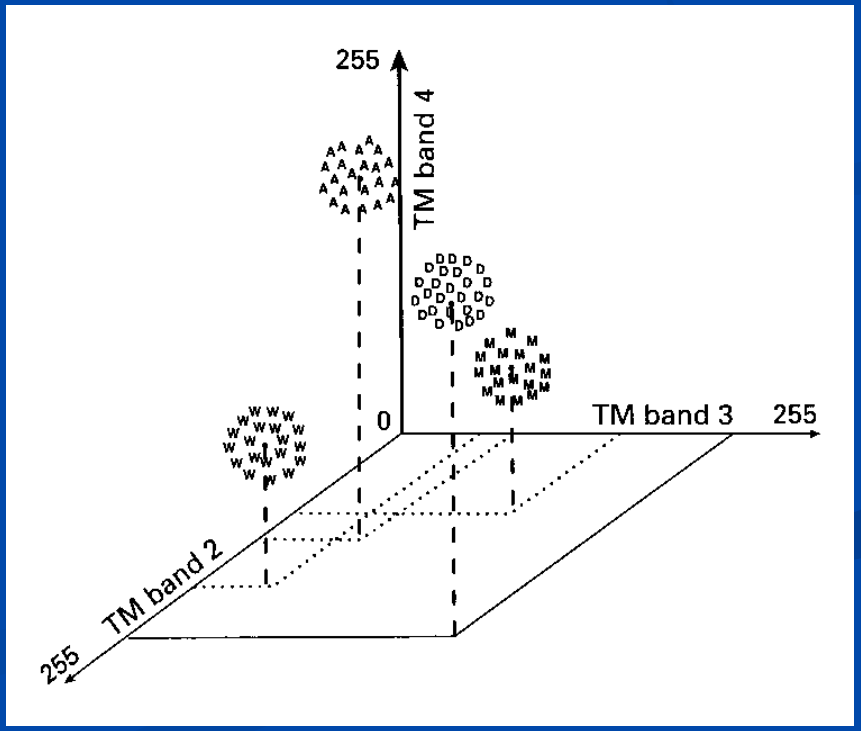
Only three compositions can be displayed at once (R,G,B)

Spectral Classification



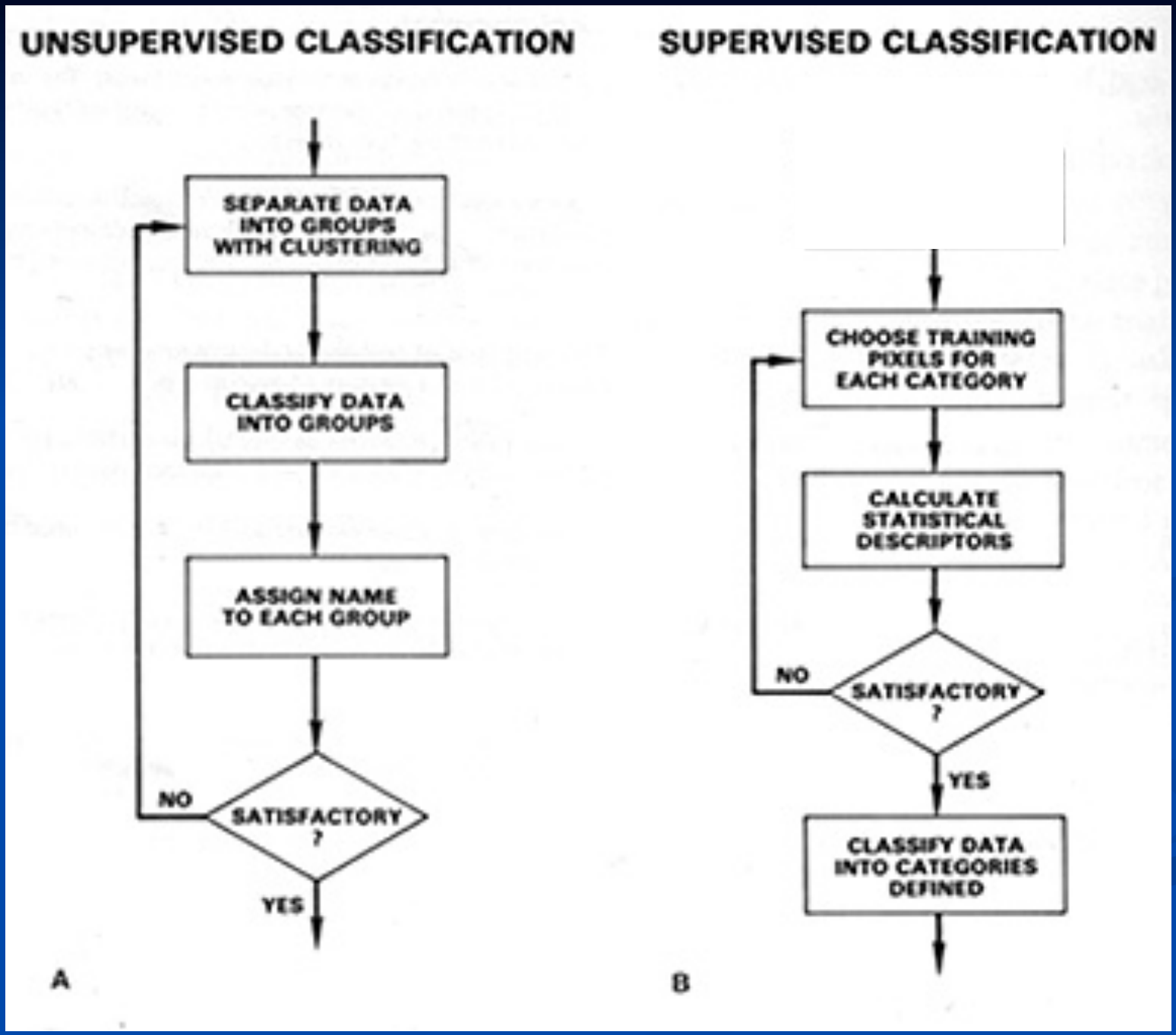
Spectral Classification





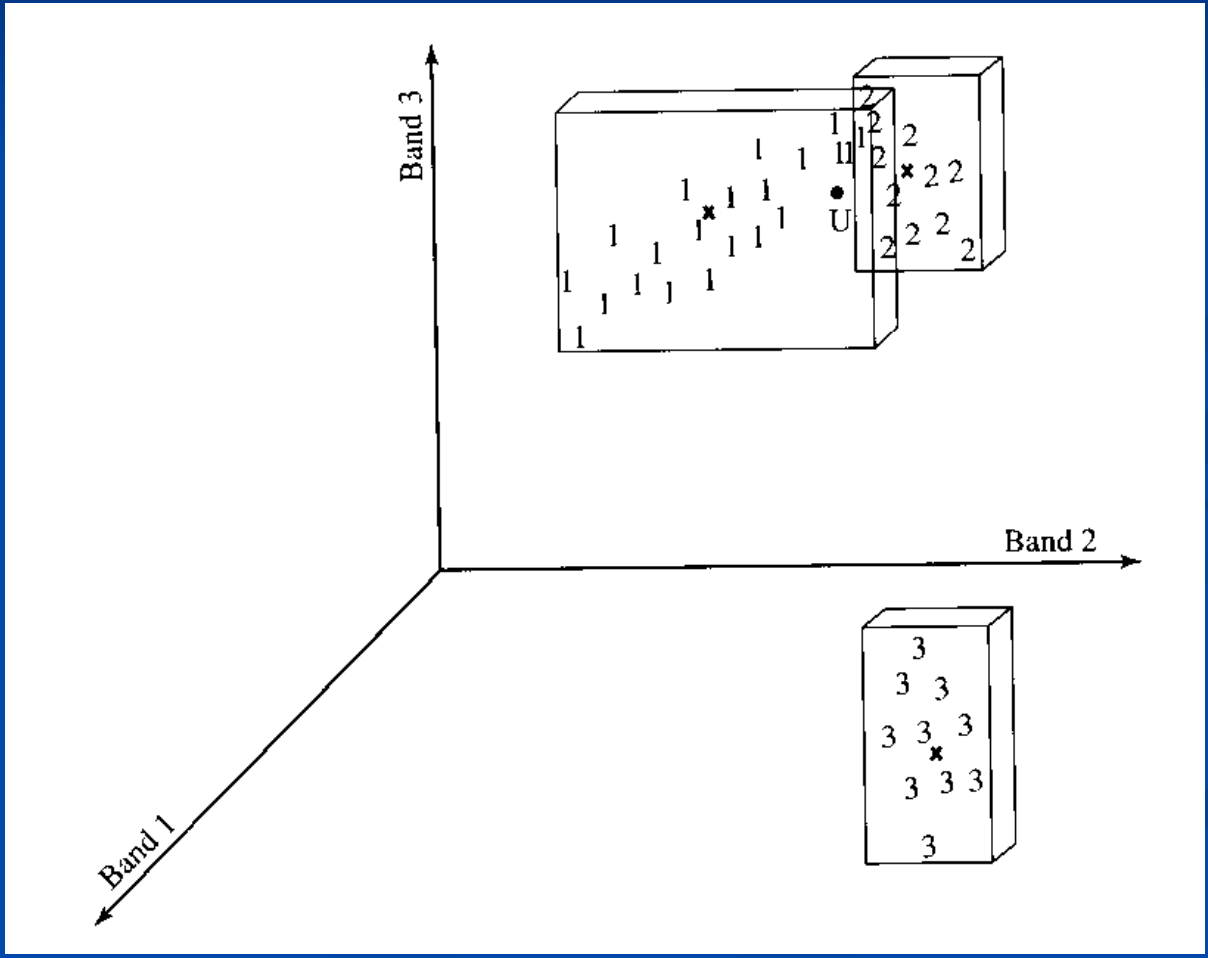
Supervised versus Unsupervised Classification

- "Unsupervised" – Classes are determined by the computer. Also referred to as "clustering"
- "Supervised" – Classes are specified by analyst, typically via extraction of spectra from training areas in the scene.

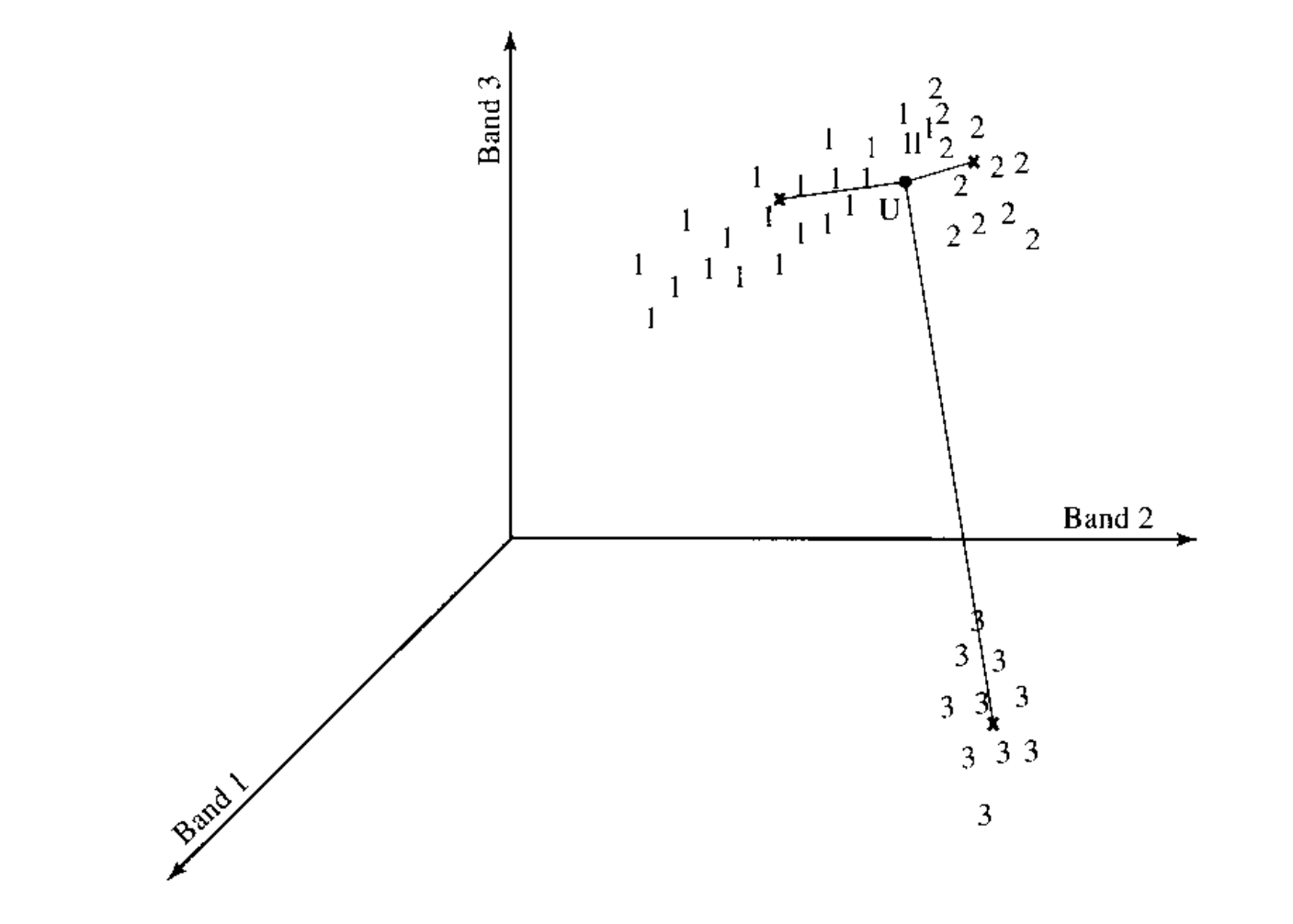

UNSUPERVISED CLASSIFICATION
SEPARATE DATA INTO GROUPS WITH CLUSTERING
CLASSIFY DATA INTO GROUPS
ASSIGN NAME TO EACH GROUP
NO
SATISFACTORY ?
YES
A
SUPERVISED CLASSIFICATION
CHOOSE TRAINING PIXELS FOR EACH CATEGORY
CALCULATE STATISTICAL DESCRIPTORS
NO
SATISFACTORY ?
YES
CLASSIFY DATA INTO CATEGORIES DEFINED
B

Supervised Classifications
(all available in ENVI!)

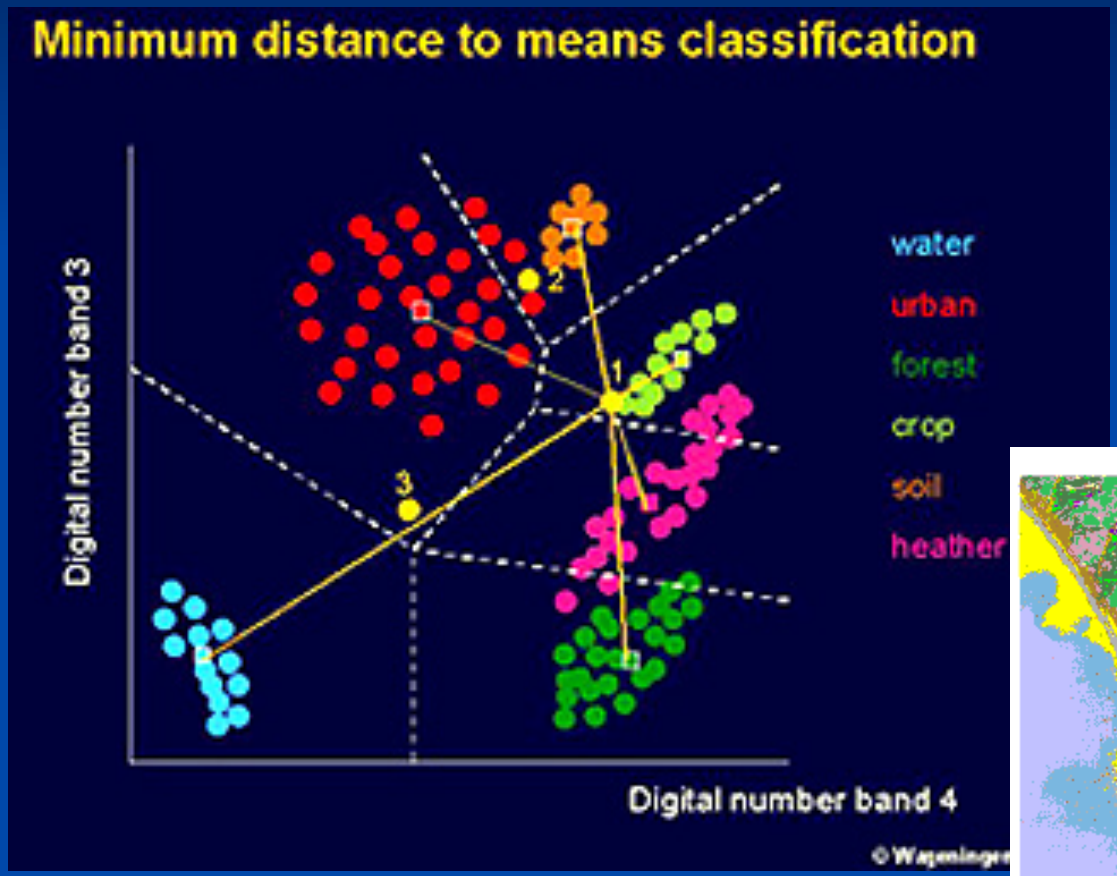
Parallelepiped

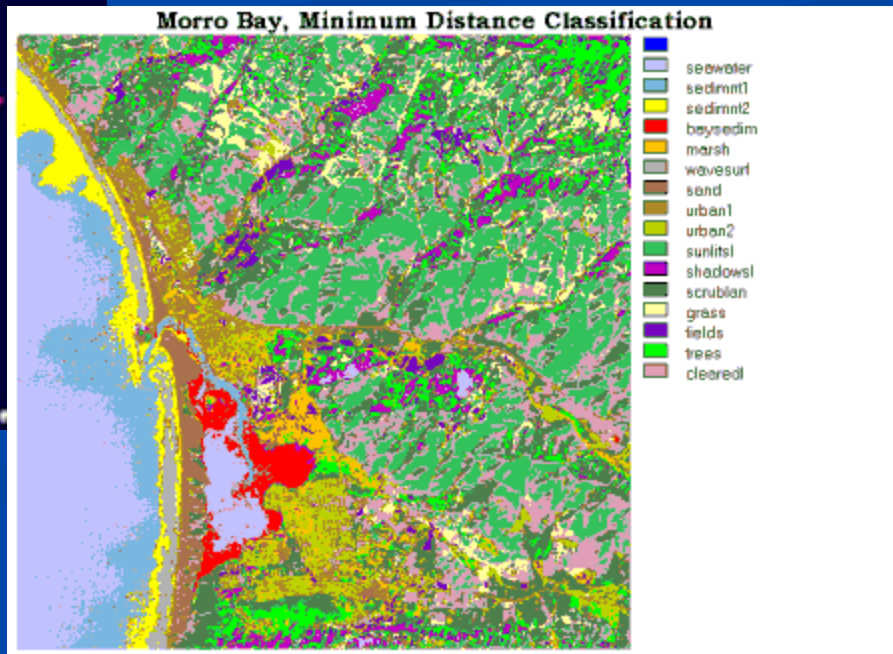


Minimum Distance

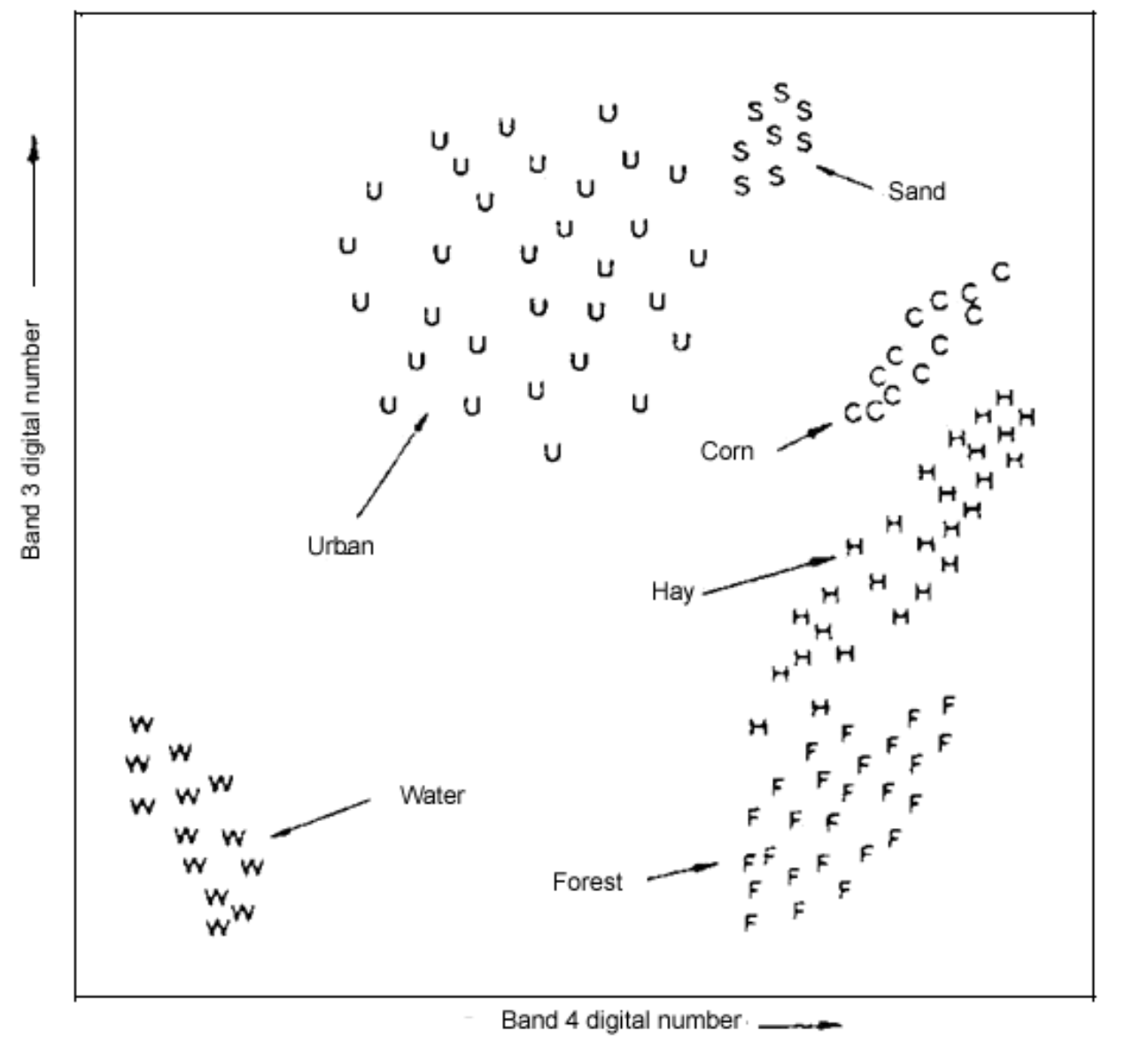


Minimum Distance Method

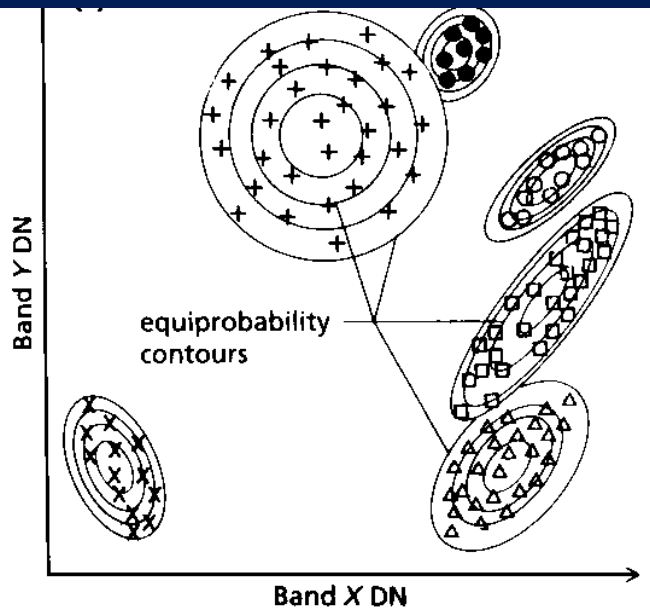


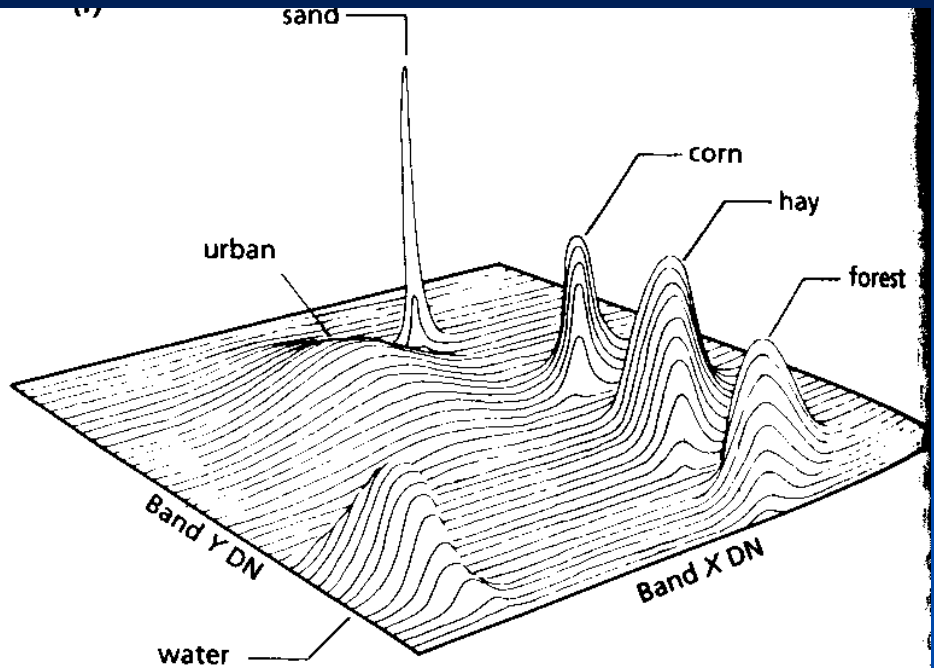


Maximum Likelihood



Maximum Likelihood





Key

corn

forest

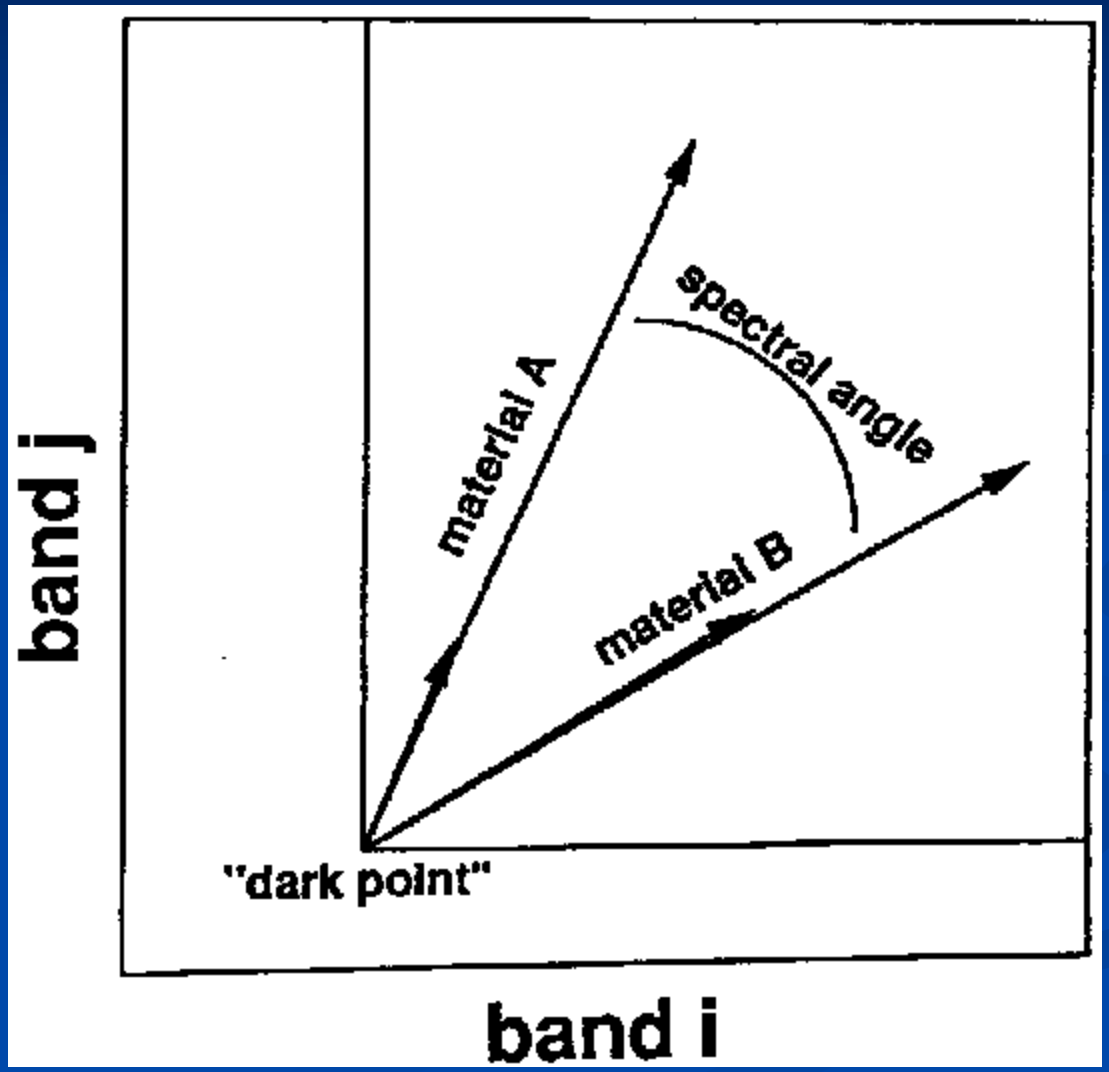
hay

sand

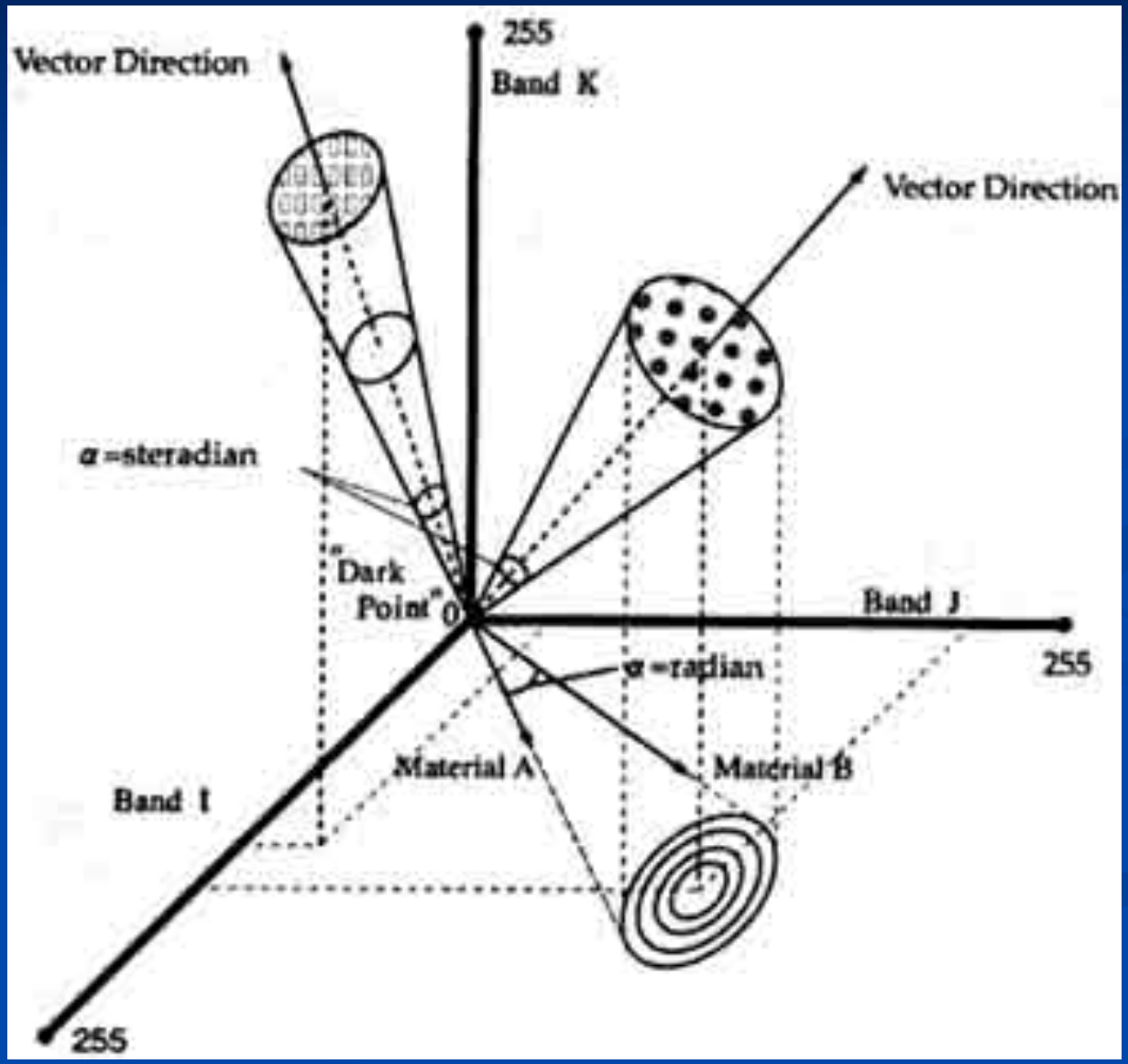
urban

water

Spectral Angle Mapper



Spectral Angle Mapper

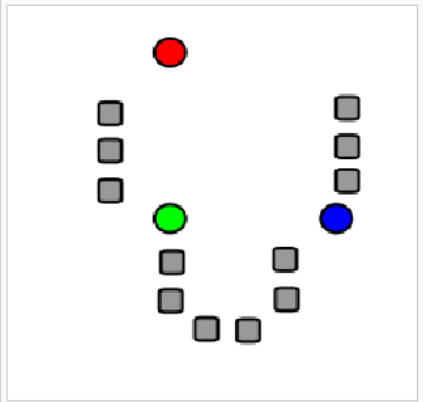


Unsupervised Techniques: K-Means

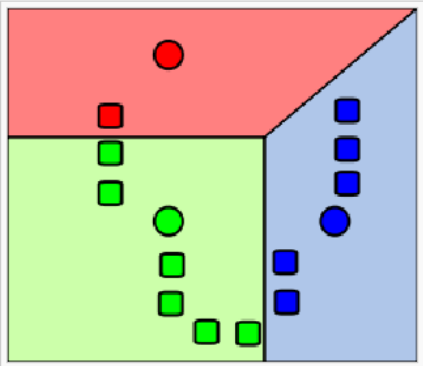
- User specifies # of classes. Algorithm first assigns randomly distributed class centers in n-D space, clusters pixels according to min. distance. Next iteration, finds mean coordinates of clusters, uses these locations as new class centers and re-clusters by distance. Continues until means move less than a specified threshold between subsequent iterations.

Most useful when you know the number of spectral units in a scene a priori, but don't necessarily know where they fall within the scene (so supervised techniques aren't possible).

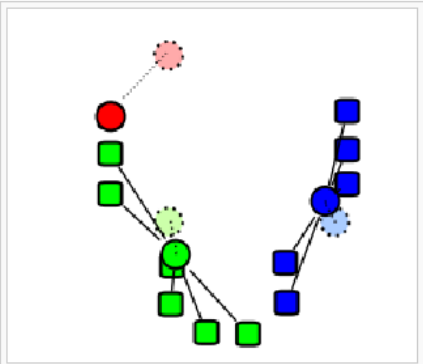
K-Means



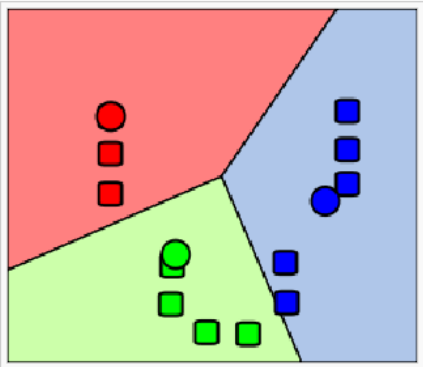
Shows the initial randomized centroids and a number of points.



Points are associated with the nearest centroid.



Now the centroids are moved to the center of their respective clusters.



Steps 2 & 3 are repeated until a suitable level of convergence has been reached.

Demo:

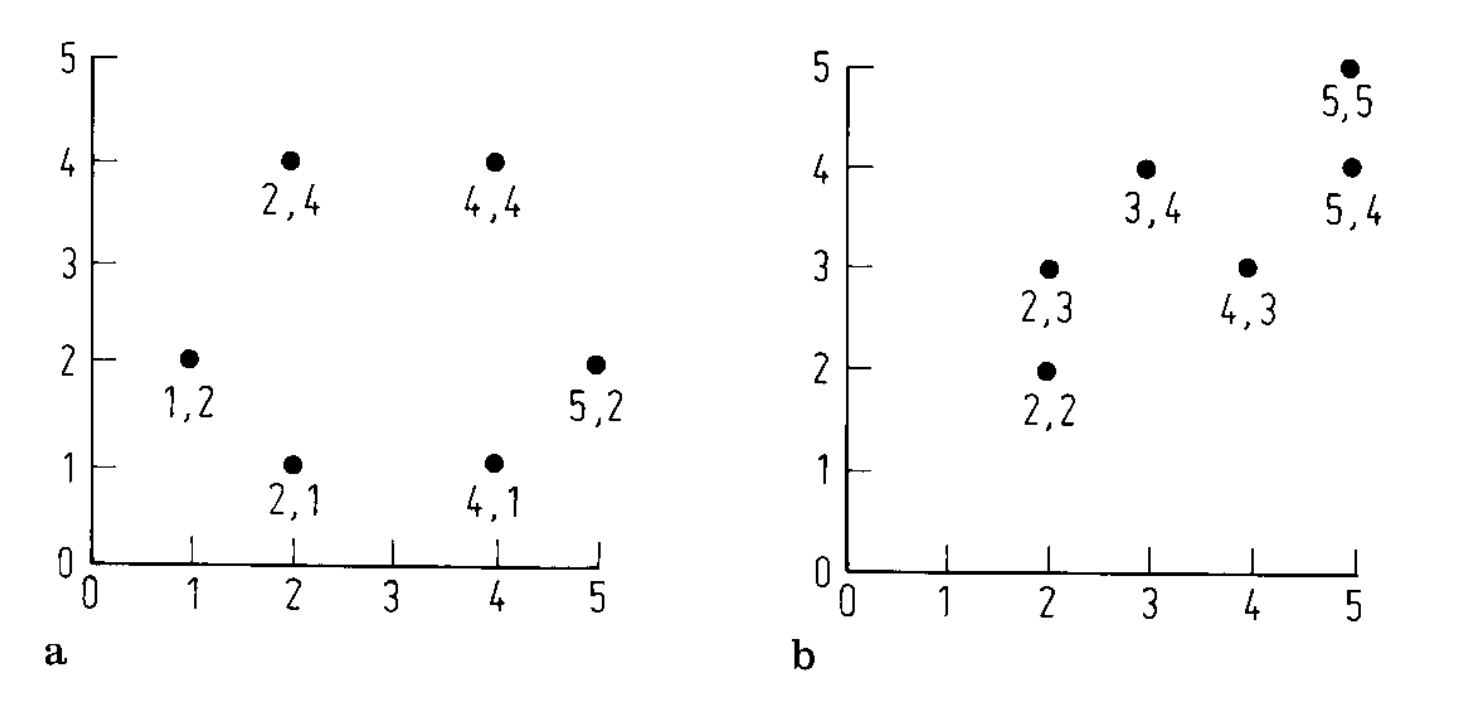
http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/AppletKM.html

Unsupervised Techniques: Isodata

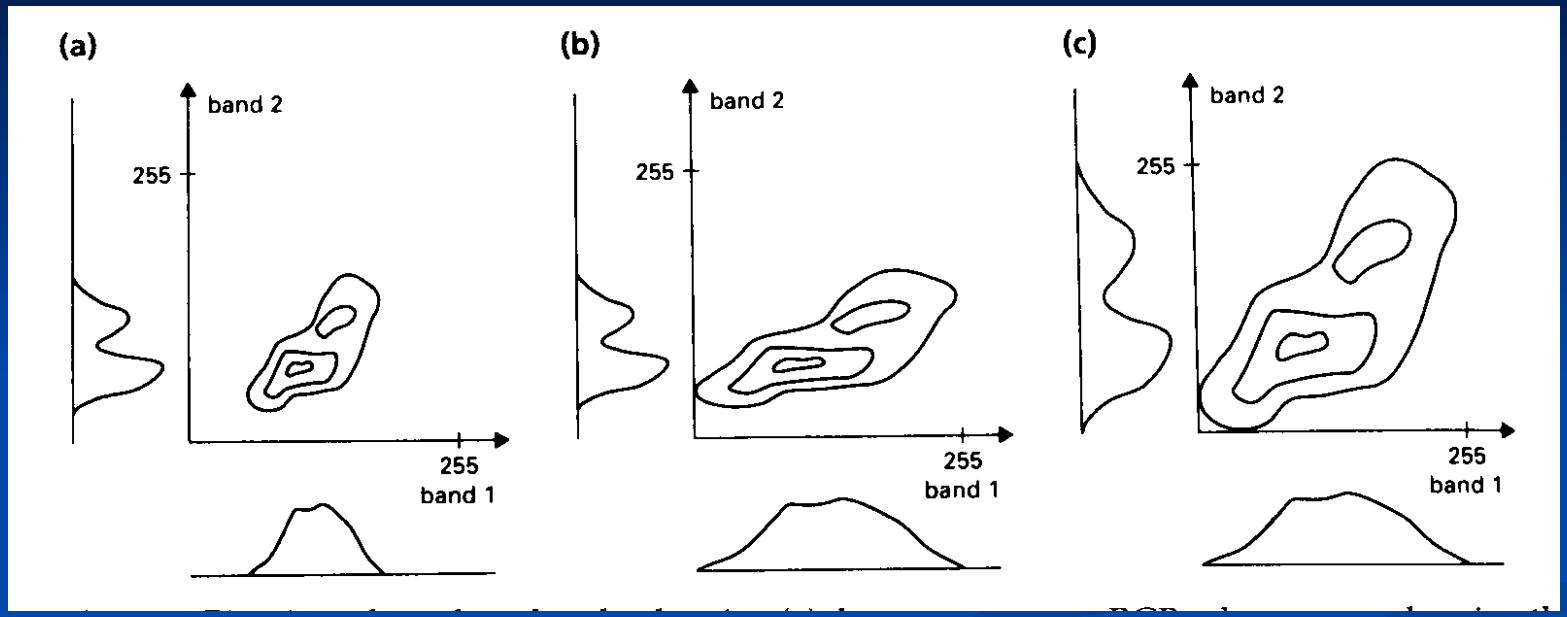
- Similar to K-means, except user doesn't need to specify number of classes. Algorithm starts with randomly spaced trial classes, calculates minimum distances to cluster all pixels in the scene. Before next iteration, algorithm looks at the statistics of each class to see if any should be split, merged, or deleted. Iterations continue until number of pixels in each class changes less than some threshold between iterations.

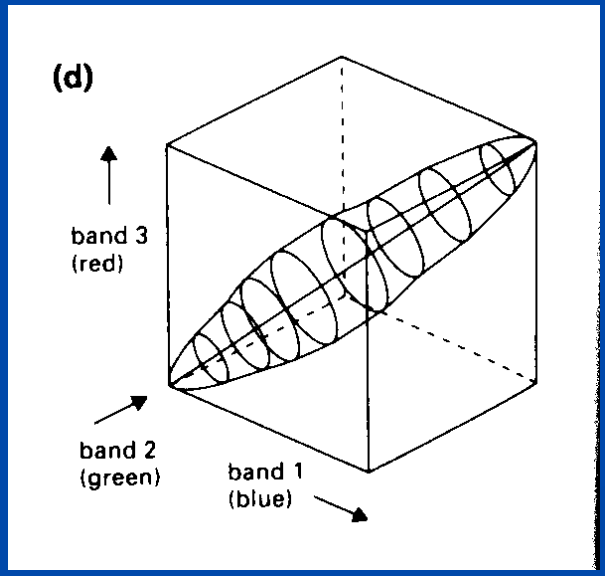
Most useful when you don't have a clue how many spectral units are likely to be present in a scene.

Correlated vs. Uncorrelated Data



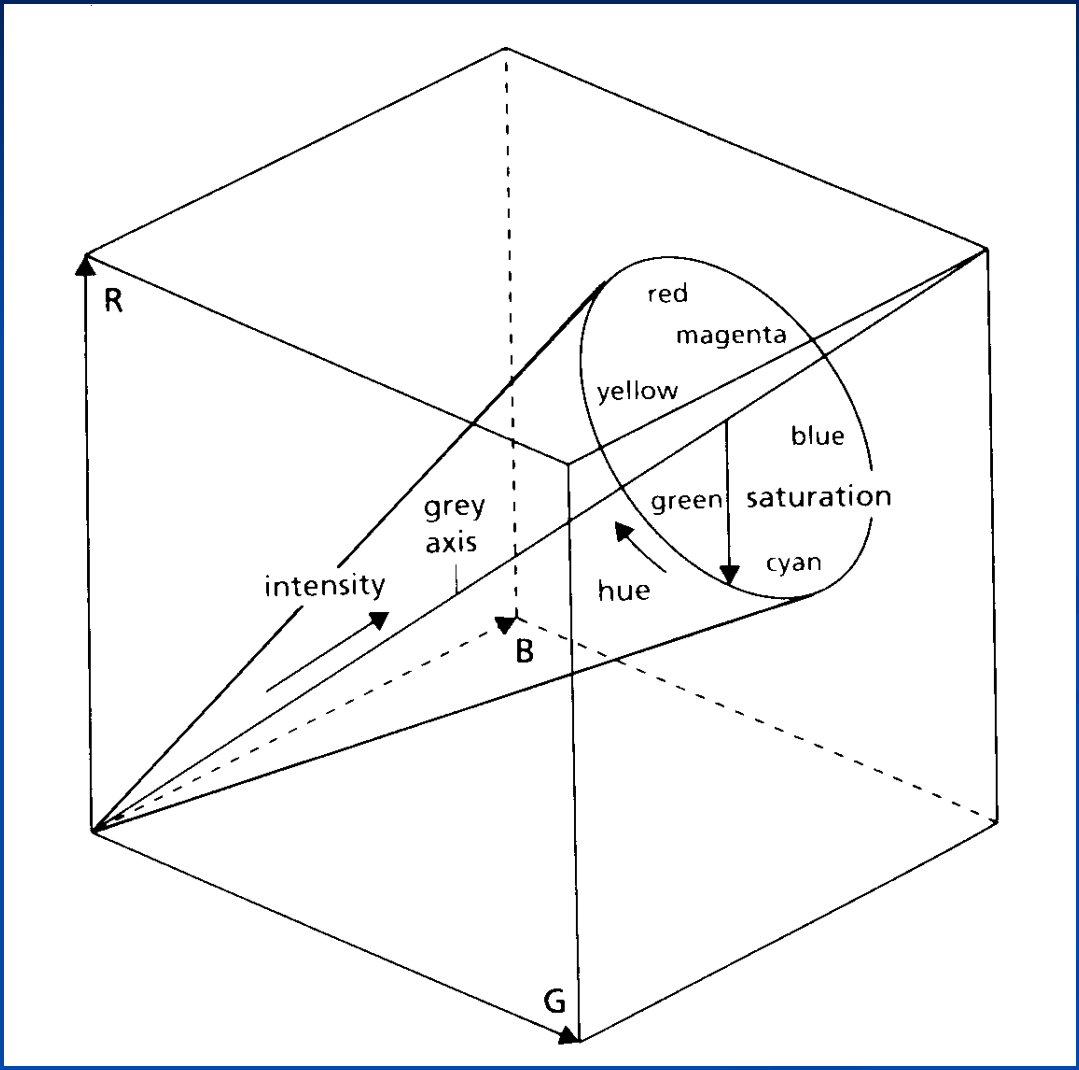
3-Band Correlations in RGB





Data only occupy a small fraction of the total colors available for display.

Intensity, Saturation, and Hue



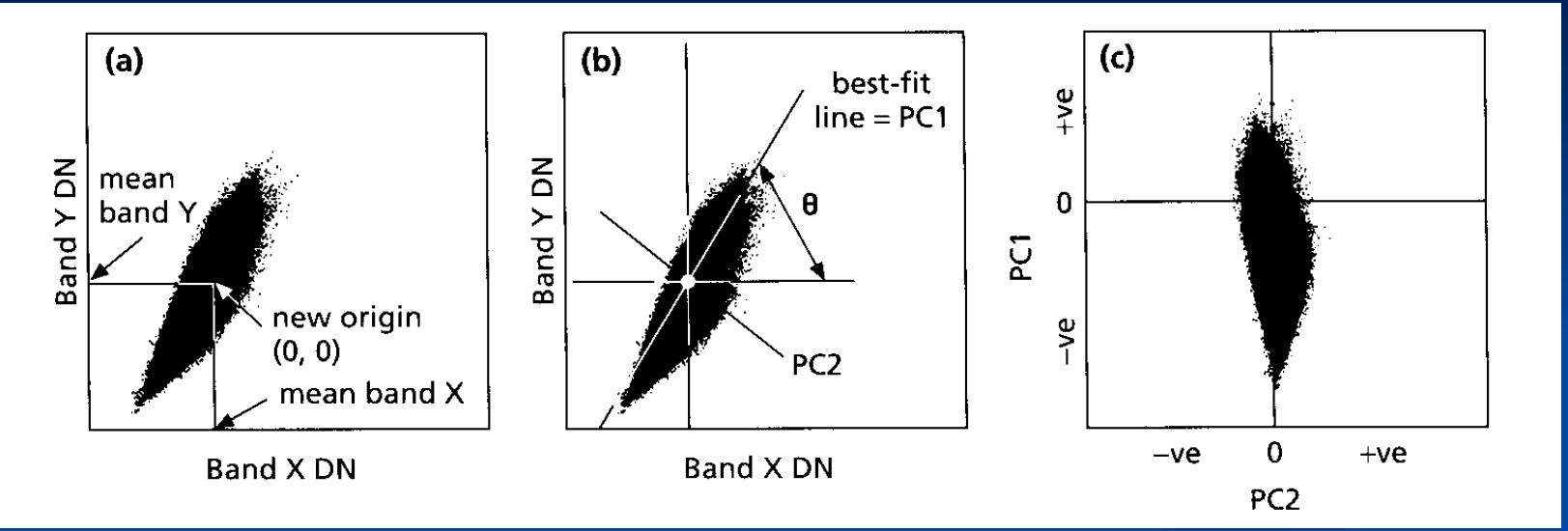
Most of the compositional information is in hue and saturation.

- An "HIS stretch" usually involves converting RGB coordinates for pixels into measures of hue, intensity, and saturation. Intensity and saturation can be stretched to more completely fill color space.
- Often, another higher spatial resolution, mono- or pan-chromatic band is used to replace the original intensity data. The lower resolution multispectral data are used to provide hue and saturation in the merged (or "fused") output image. Called "Pan-sharpening."

Principal Component Analysis (PCA)

- Multispectral, and especially hyperspectral data have more information from more wavelengths than our brains can process!
- Often, one band is highly correlated with another
- PCA offers a way to reduce the inherent "dimensionality" of a multi- or hyperspectral dataset into the smallest number of independent dimensions
- Makes contrast enhancement of different classes much better

Principal Component Analysis (PCA)



1. Move origin of coordinate system to center (mean) of data cloud.
2. Find a rotation of axes that maximizes the variance of the data along the new orientations of the axes.
3. Stretch the data along the new axes to fill the color space – points are no longer correlated.

PCA Terminology

- Eigenvector: Describes the shift and orientation of the new axes. For n input bands, you get n output bands with n associated eigenvectors

- Eigenvalue: Describes the magnitude of the variance along the new axes (prior to stretching). There is one eigenvalue for each axis.

PCA Advantages

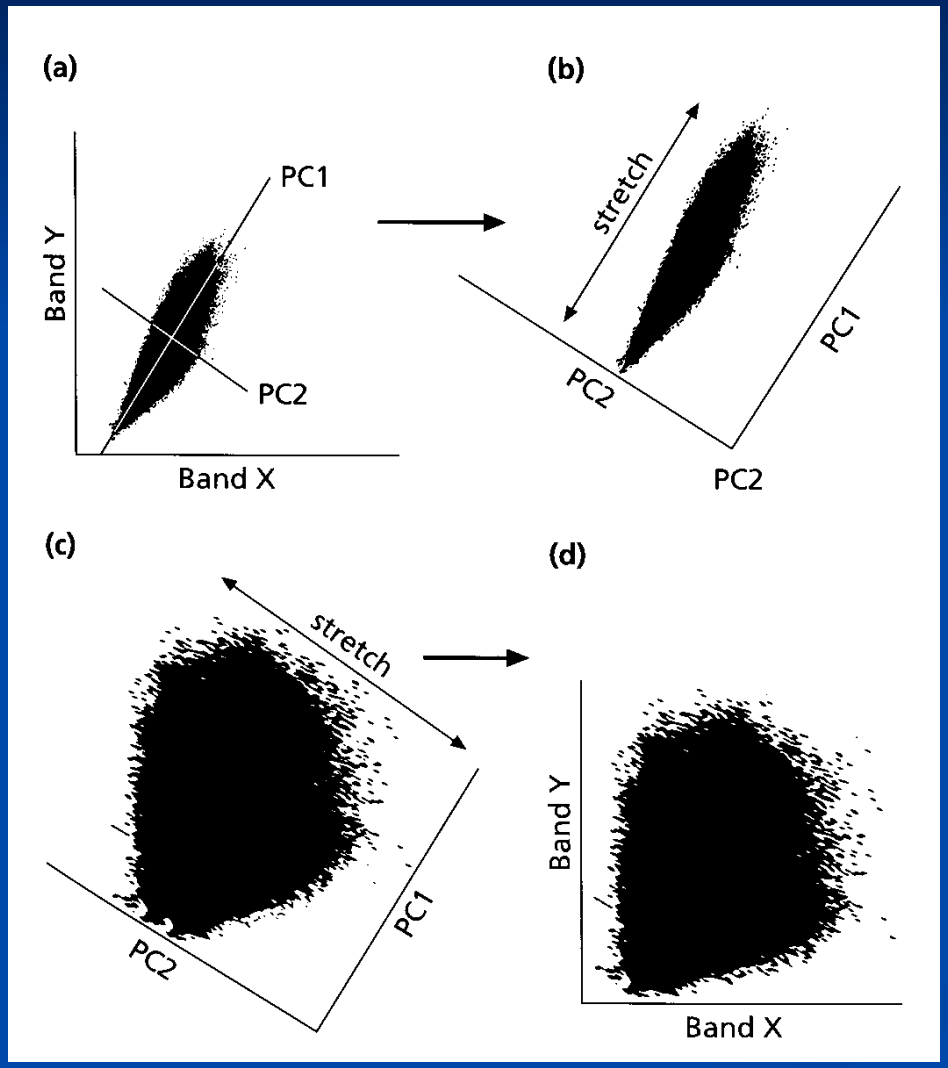
- PCA analysis can simultaneously consider all input bands.
- Has the effect of reducing the "dimensionality" of the data (fewer # of bands contain most of the information) because higher-order axes don't contain as much independent (uncorrelated) information.
- More completely fills the available color space when PCA bands are displayed in RGB triplets

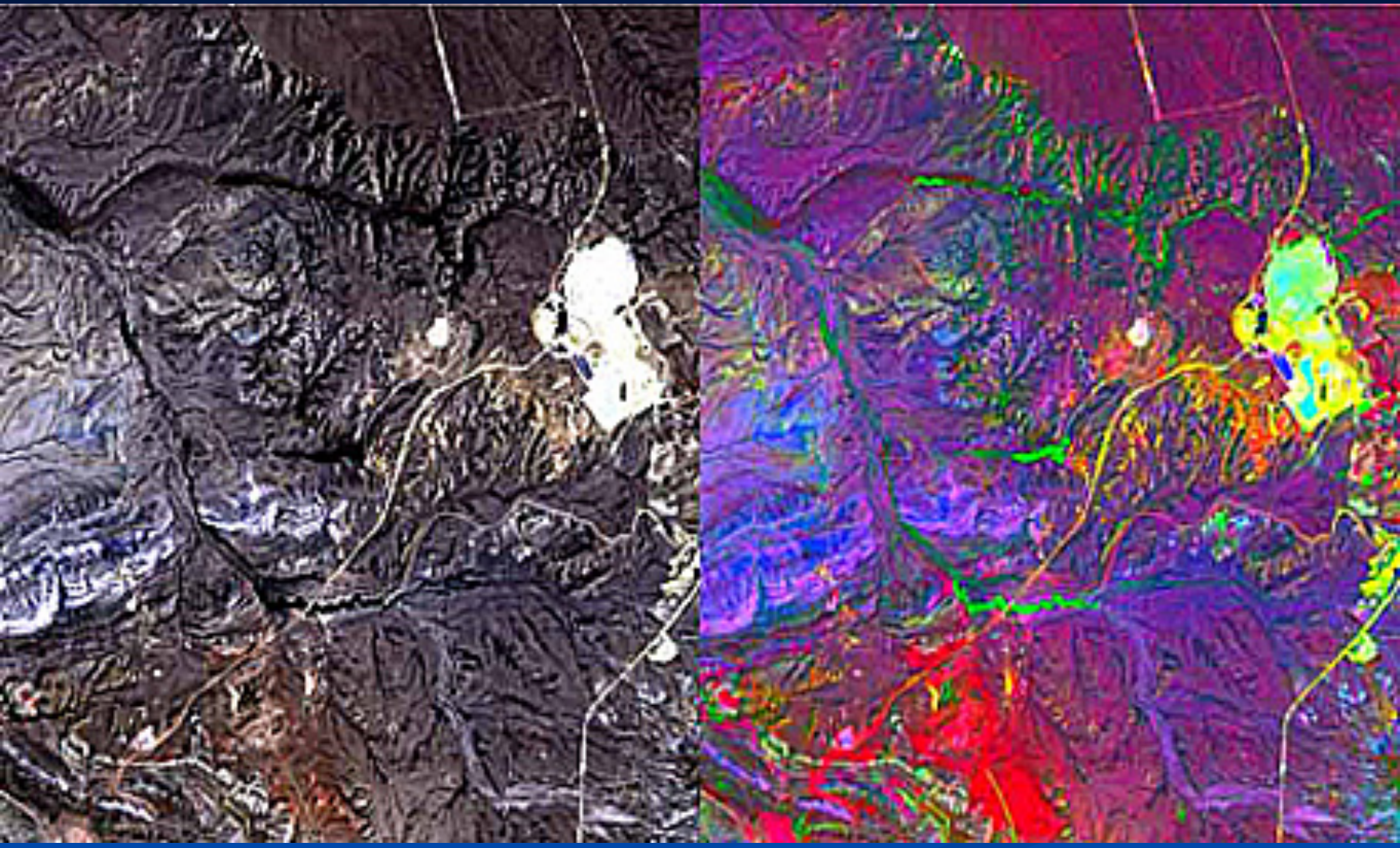
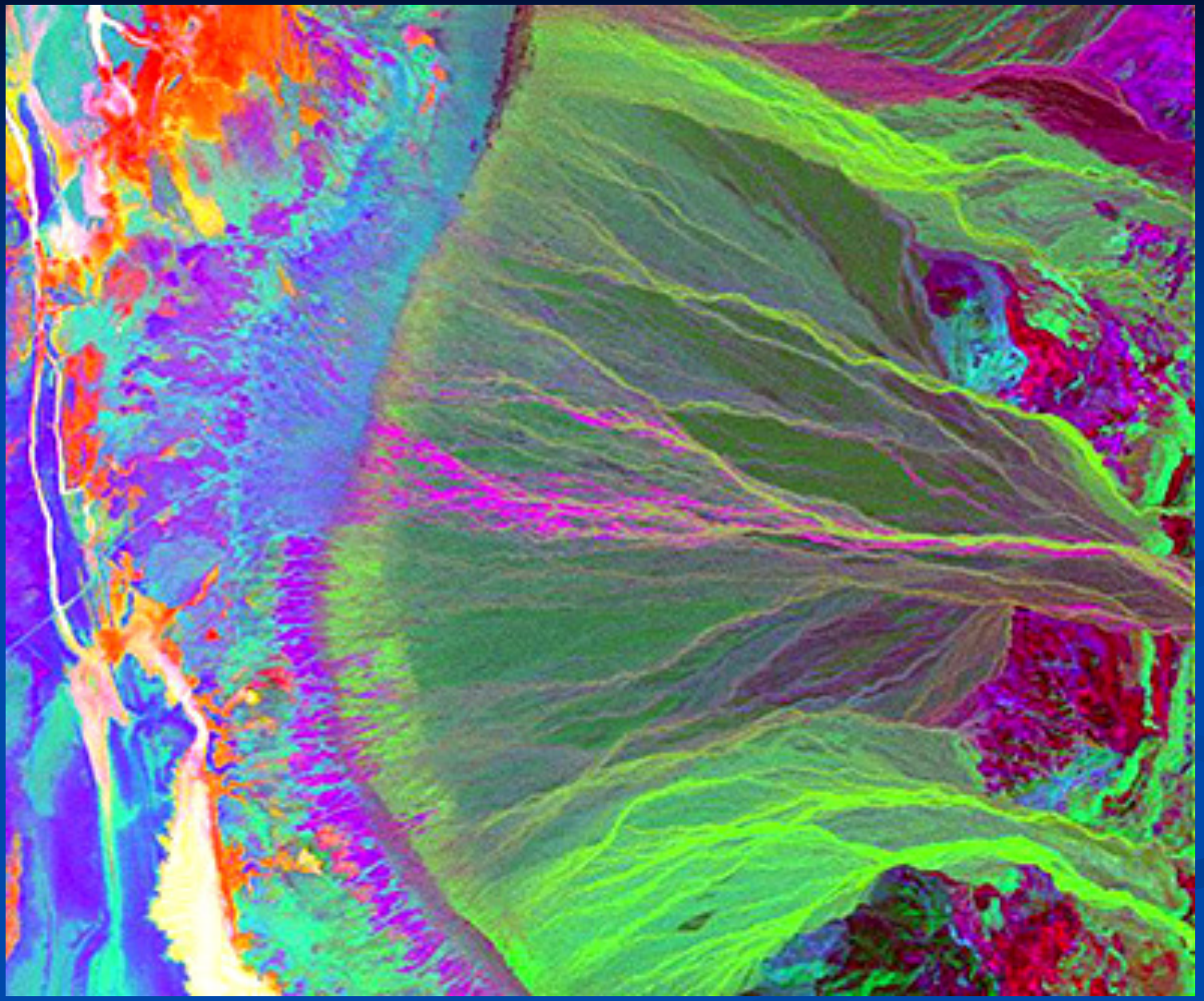
PCA Disadvantages

- Can be difficult to understand PCA bands in terms of composition – no one-to-one correspondence between a particular PCA band and any one input band.

Typically, PCA bands are used to map the spectral/ compositional units in a scene. Once the pixels belonging to a particular spectral unit have been identified, compositional identifications are made using spectra for those pixels extracted from the original input pixels (pre-PCA).

Decorrelation Stretching



After performing a PCA rotation and stretching the data, the axes are rotated back to their original (input) orientations.

Preserves original sense of "color."