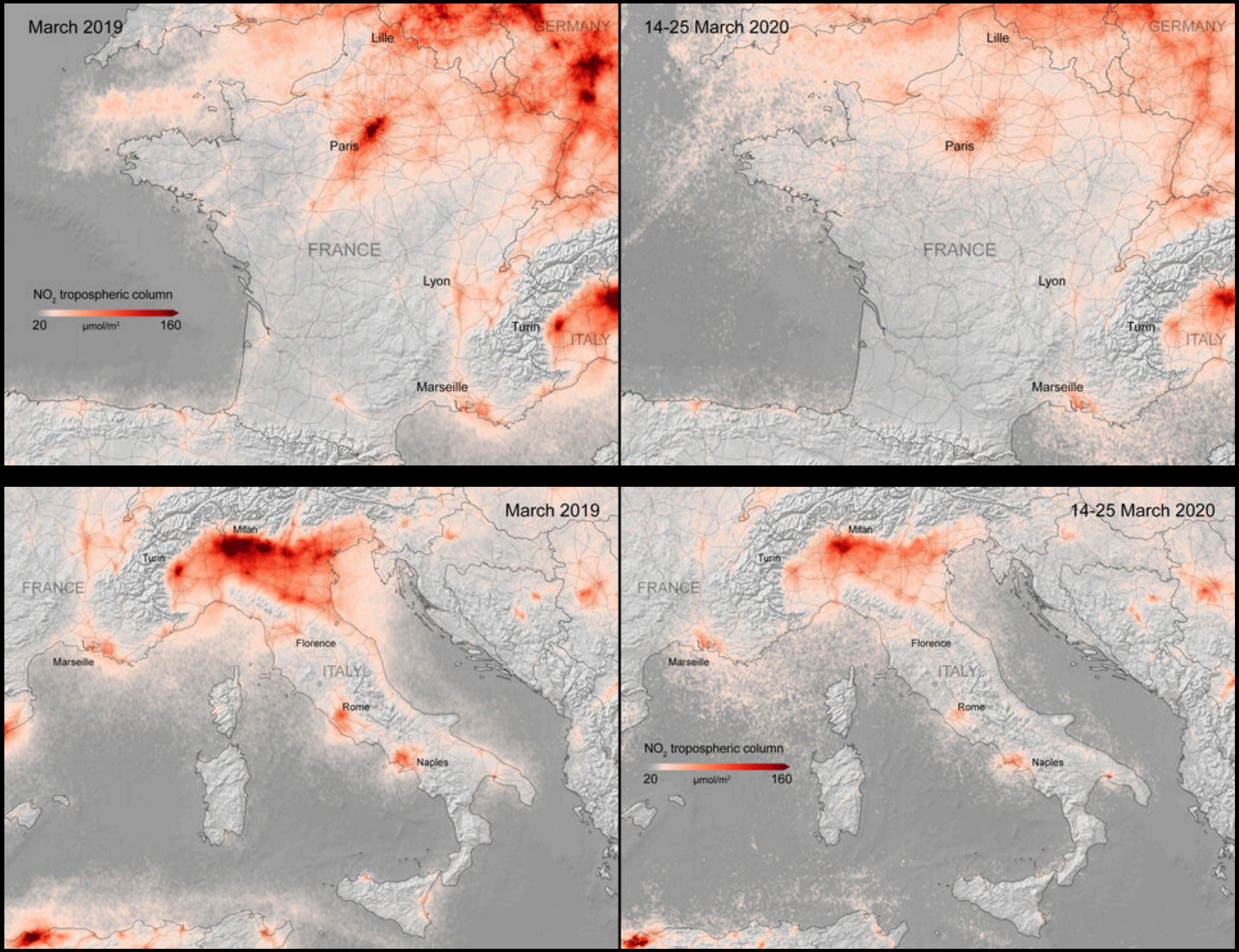
Data of the Week

Sentinel-5 TROPOMI



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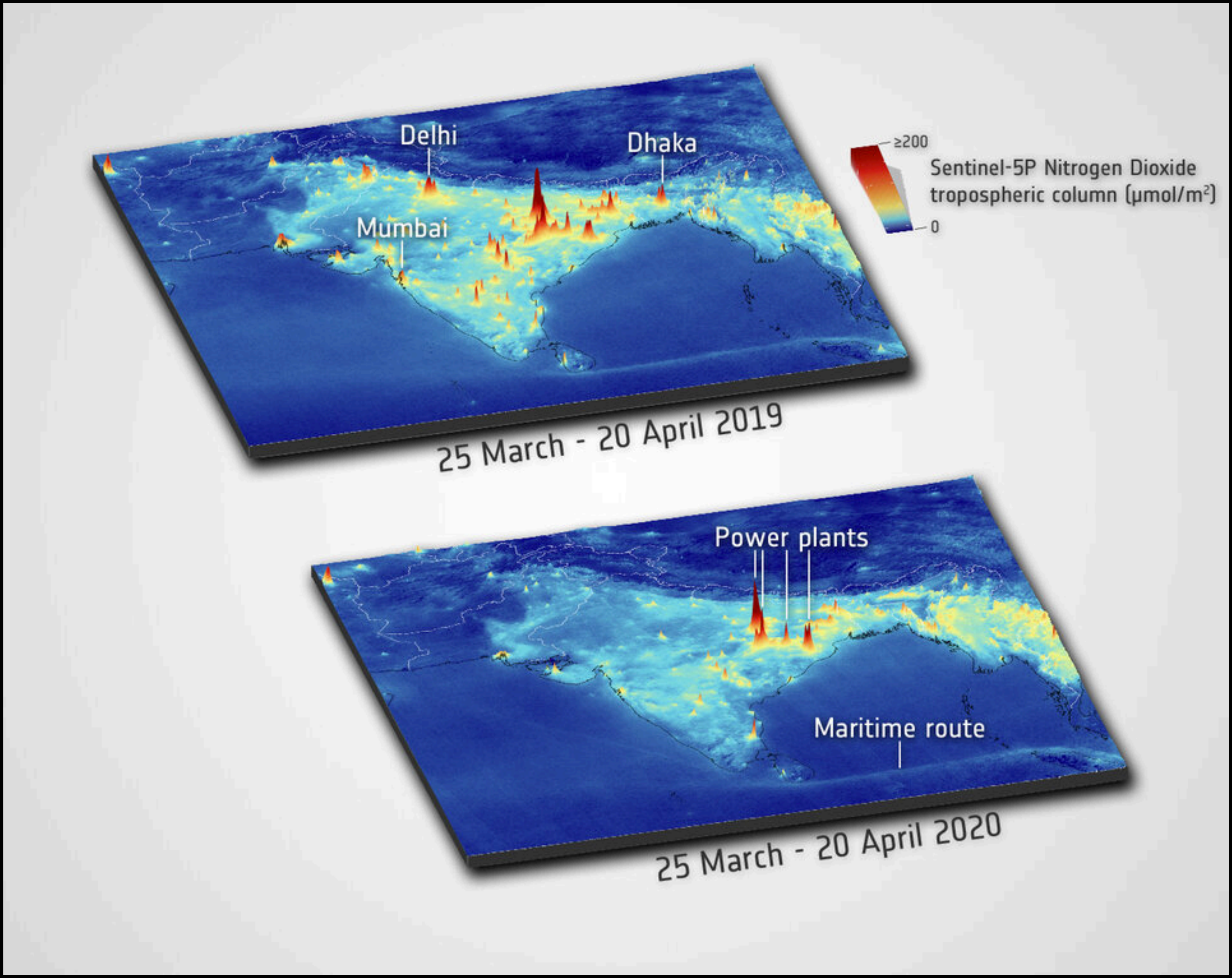
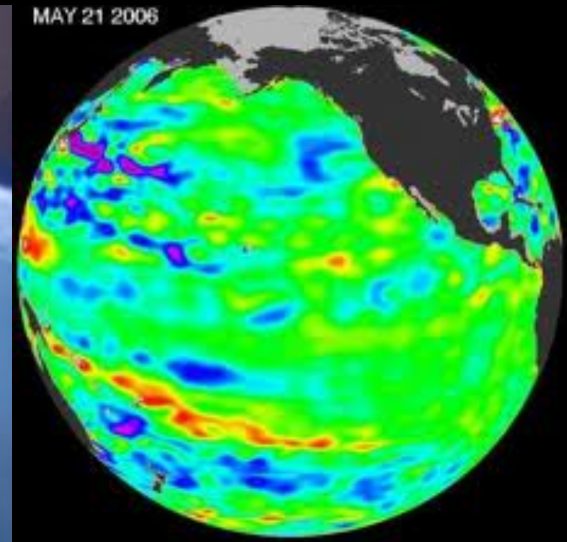
Sentinel-5 TROPOMI



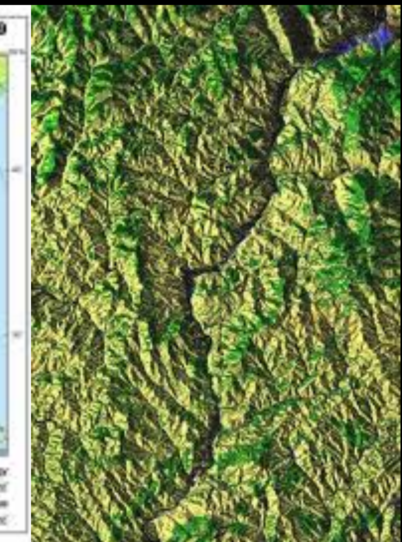



Image Analysis (1)

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EVSC 4010/7010 Week 6

Why image analysis

- Big data: finding patterns and information
- Classification: urban planning, conservation
- Change detection: geography, economics, forestry

Landsat 5

Landsat 8

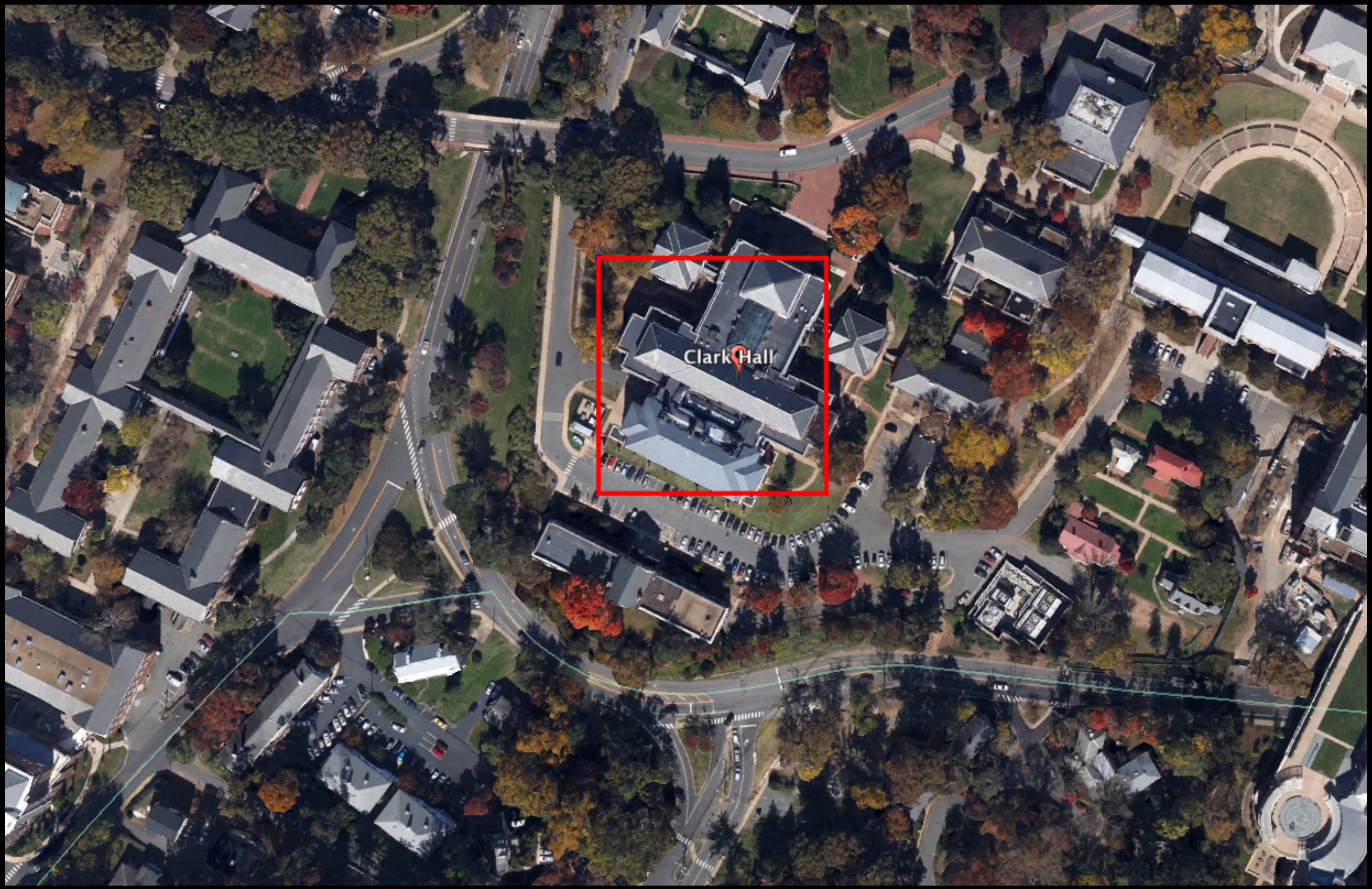
Week 6 & 7 Outline

- Principle Component Analysis (PCA) and Tasseled Cap Transformation (TCT)
- Spectral Mixture Analysis (SMA)
- Land use/cover classification
- Change detection and time-series analysis

Pure vs. Mixed Pixels

- In the class, so far, we have mainly considered *pure* pixels (e.g. pixels in which there is one type of material).
- When do you find pure pixels?
  - When the spatial extent of the material is larger than the size of the pixel. Examples:
    - Large clouds, 1 km MODIS pixels
    - Leaves and laboratory setting with a spectrometer
  - Much of the time, we must instead deal with mixtures

Mixed pixels

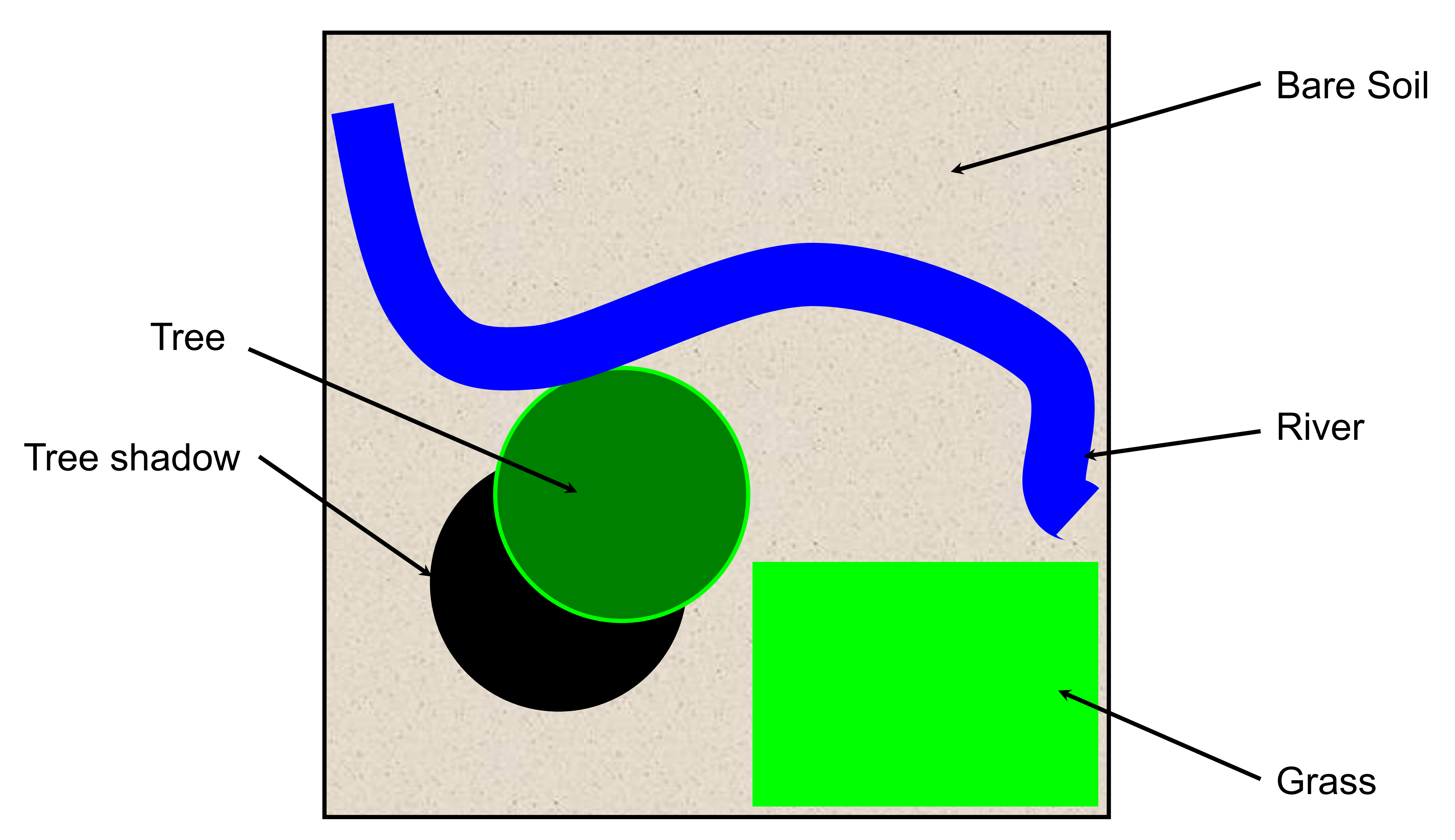


~80% Building
~10% Shadow
~5% Vegetation
~5% Road

A pixel contains different materials, many have different spectra.

- What are the components present in a pixel, and how much of a pixel is comprised of a given component?
- How many unique components in a pixel can be identified?

A conceptual mixed pixel

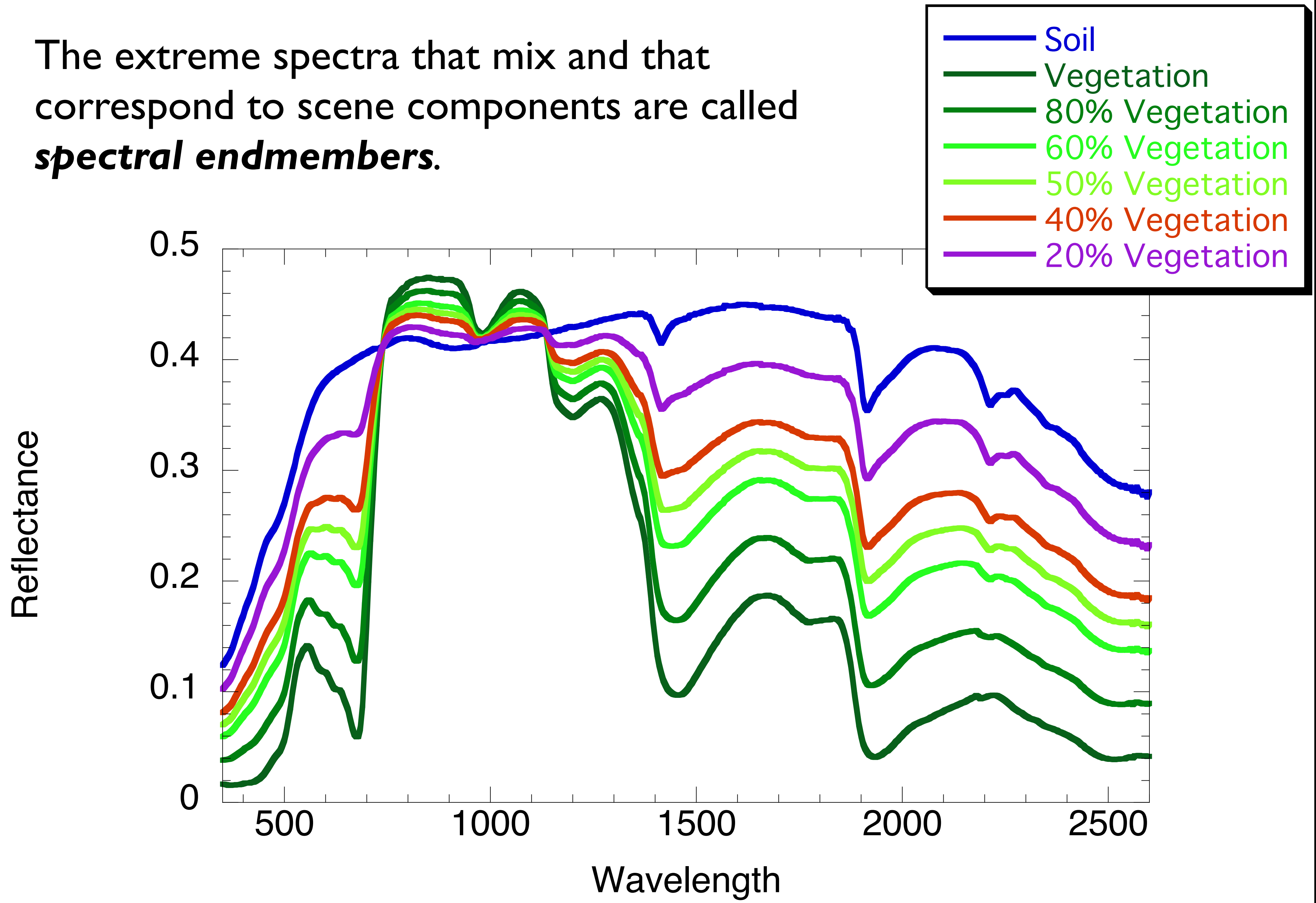


- The reflectance of the pixel is the combination of the reflectance of each type in that pixel, in proportion to the area they occupy.

Spectral Mixture Analysis (SMA)

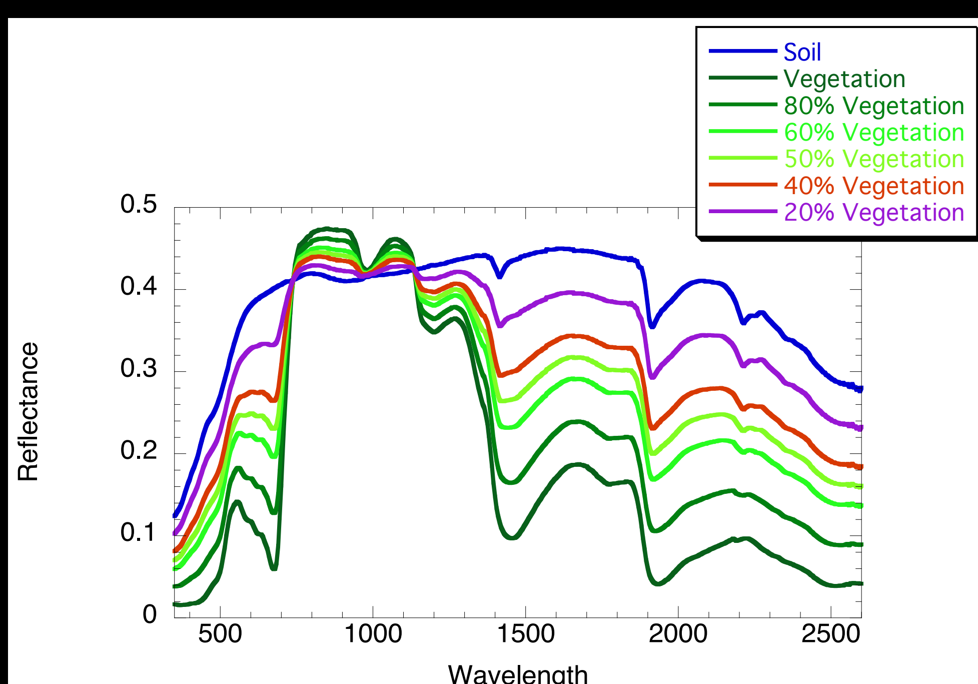
Spectral Mixture Analysis works with mixed pixels to estimate mixing fractions for each pixel in a scene.

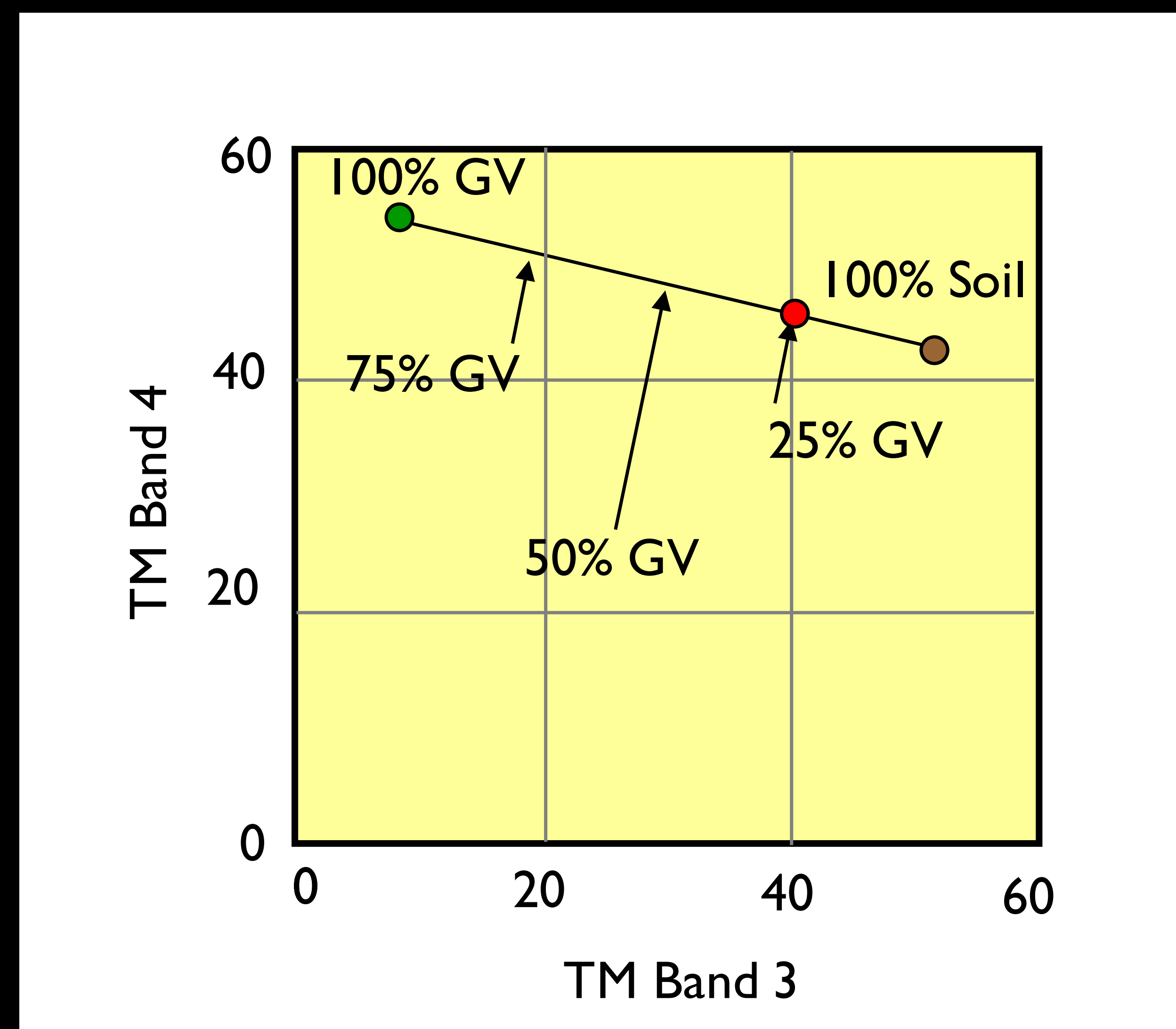
The extreme spectra that mix and that correspond to scene components are called ***spectral endmembers***.



An example of SMA

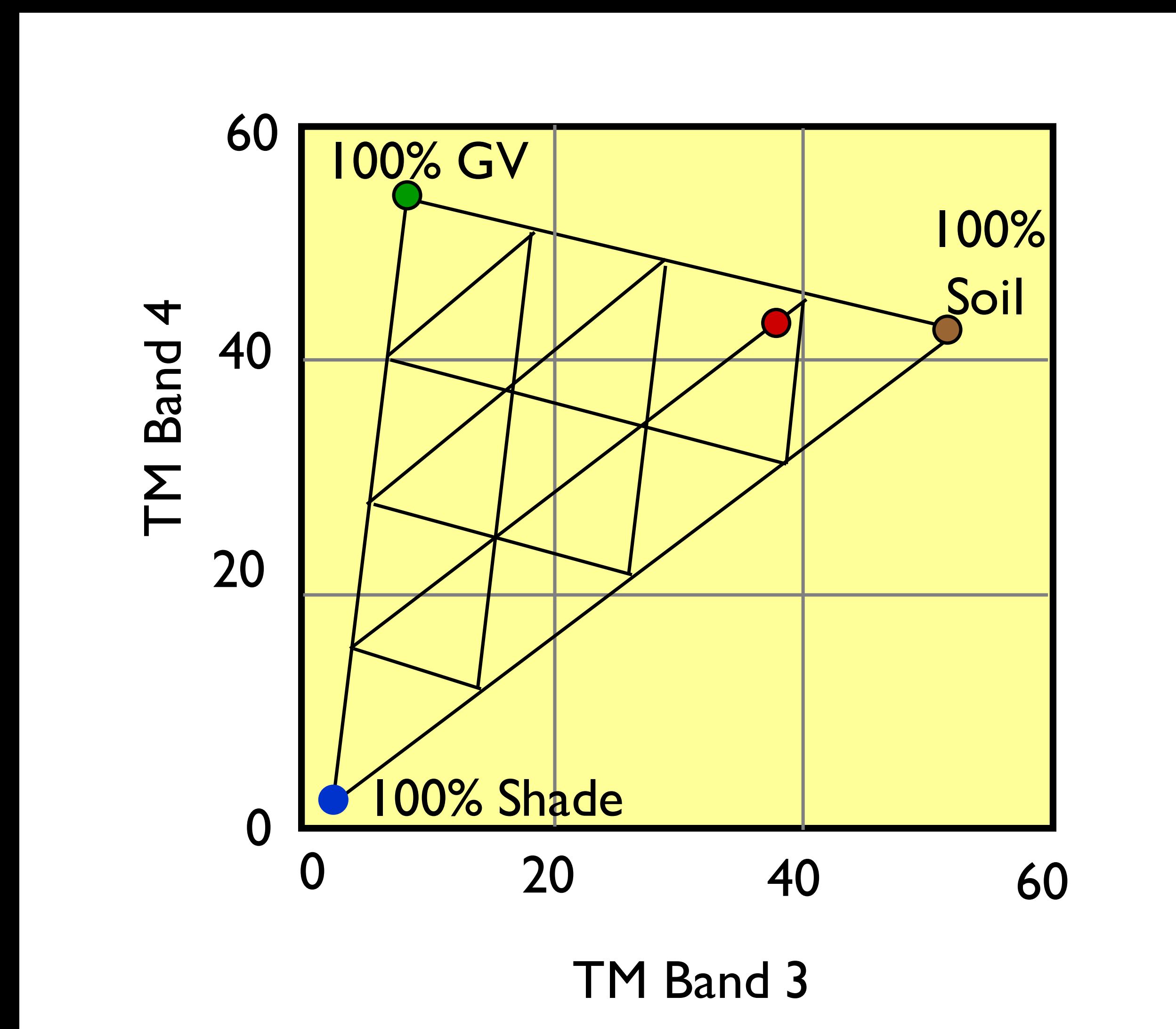
25% Green Vegetation (GV)
75% Soil





Adding the third component

25% Green Vegetation (GV)
70% Soil
5% Shade



Unmixing pixels

- We want to determine the % fraction of each endmember in a potentially mixed pixel. THIS IS AREAL FRACTION!
  - **Endmember**: pure reflectance spectra of a pixel component, measured in the lab, in the field, or from the image itself.
  - Examples of commonly used endmembers: green vegetation, soil, shadow, water, clouds, non-photosynthetic vegetation ("NPV", wood, decayed leaves, etc.)

Linear Spectral Unmixing

- Basic assumption: the reflectance of a pixel is a linear combination of the endmember spectra times their relative **cover** fraction.
- Two parts to the algorithm:

$$\sum_{i=1}^{N} F_i = F_1 + F_2 + \ldots + F_N = 1$$

Sum to 100%: endmembers must collectively "explain" the pixel

$$\rho_\lambda = F_1\rho_{\lambda,1} + F_2\rho_{\lambda,2} + \ldots + F_N\rho_{\lambda,N} + E_\lambda$$

Best-fit fractions (and error) are calculated for each DN value for each band of each pixel

F_i=fraction of endmember *i* in pixel (usually $0 \le F_i \le 1$)
ρ_λ=the pixel reflectance for band λ
$\rho_{\lambda,1}$=the reflectance for band λ of endmember 1
E_λ=error term for band λ

Solutions to the linear equations

- Note the unknowns are the fractions F. The knowns are the reflectance of each endmember in each band. For the equation below, there are **three** scenarios:

$$\rho_{\lambda} = F_1\rho_{\lambda,1} + F_2\rho_{\lambda,2} + ... + F_N\rho_{\lambda,N} + E_{\lambda}$$

  - NB+1<NE: This is a underdetermined system. The equations do not have a unique solution if there are more endmembers than band + 1;
  - NB+1=NE: The equations are solvable, but without the error term;
  - NB+1>NE: The equations are solvable, with the error term.

  - How to determine the reflectance of each endmember?

Finding the endmembers

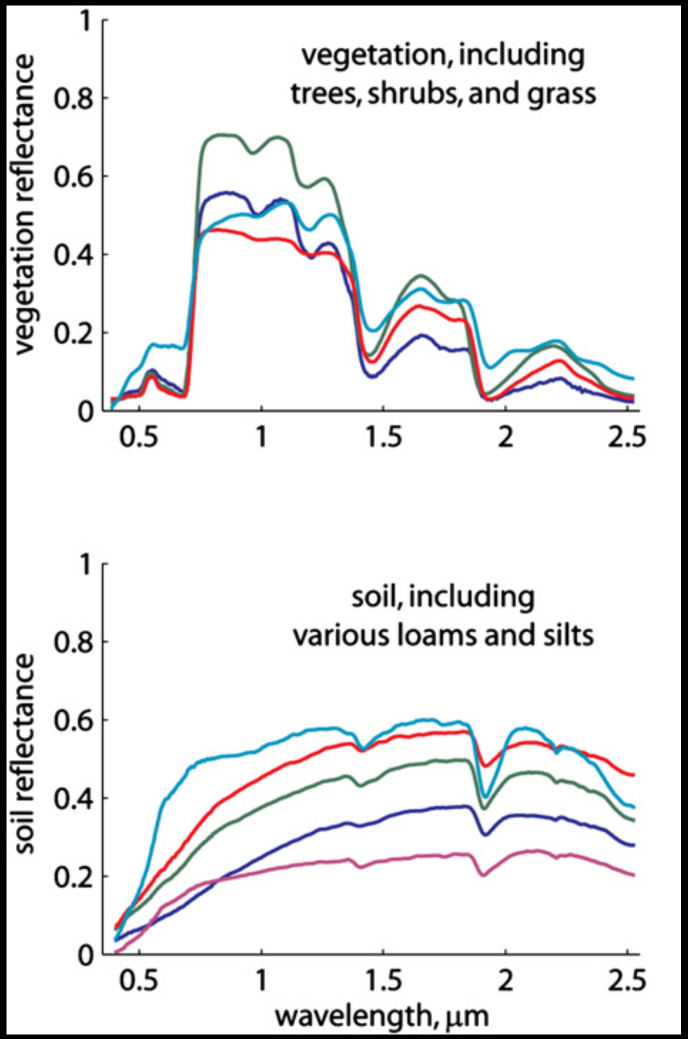


Image Endmembers

Library Endmembers

An example

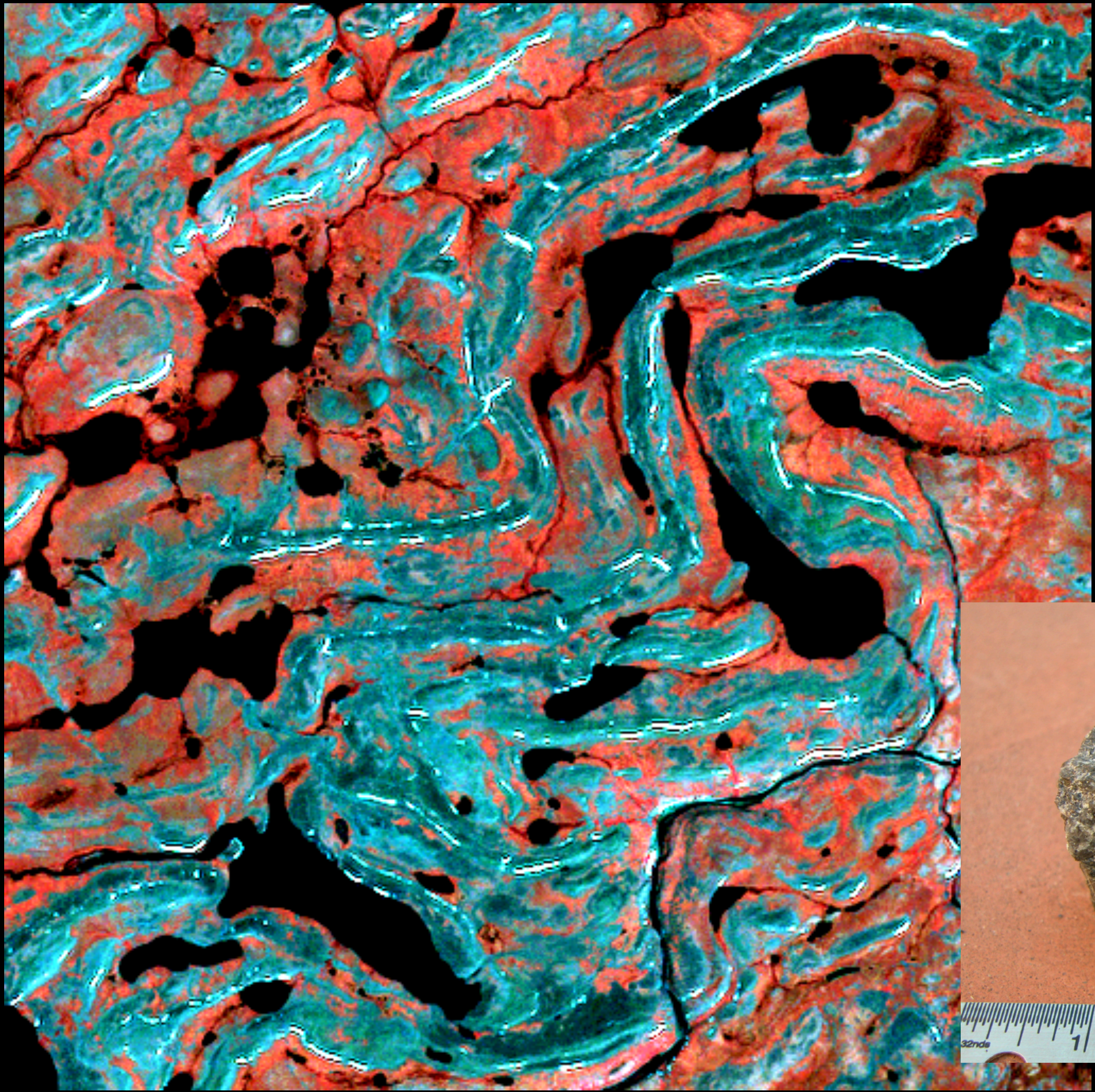
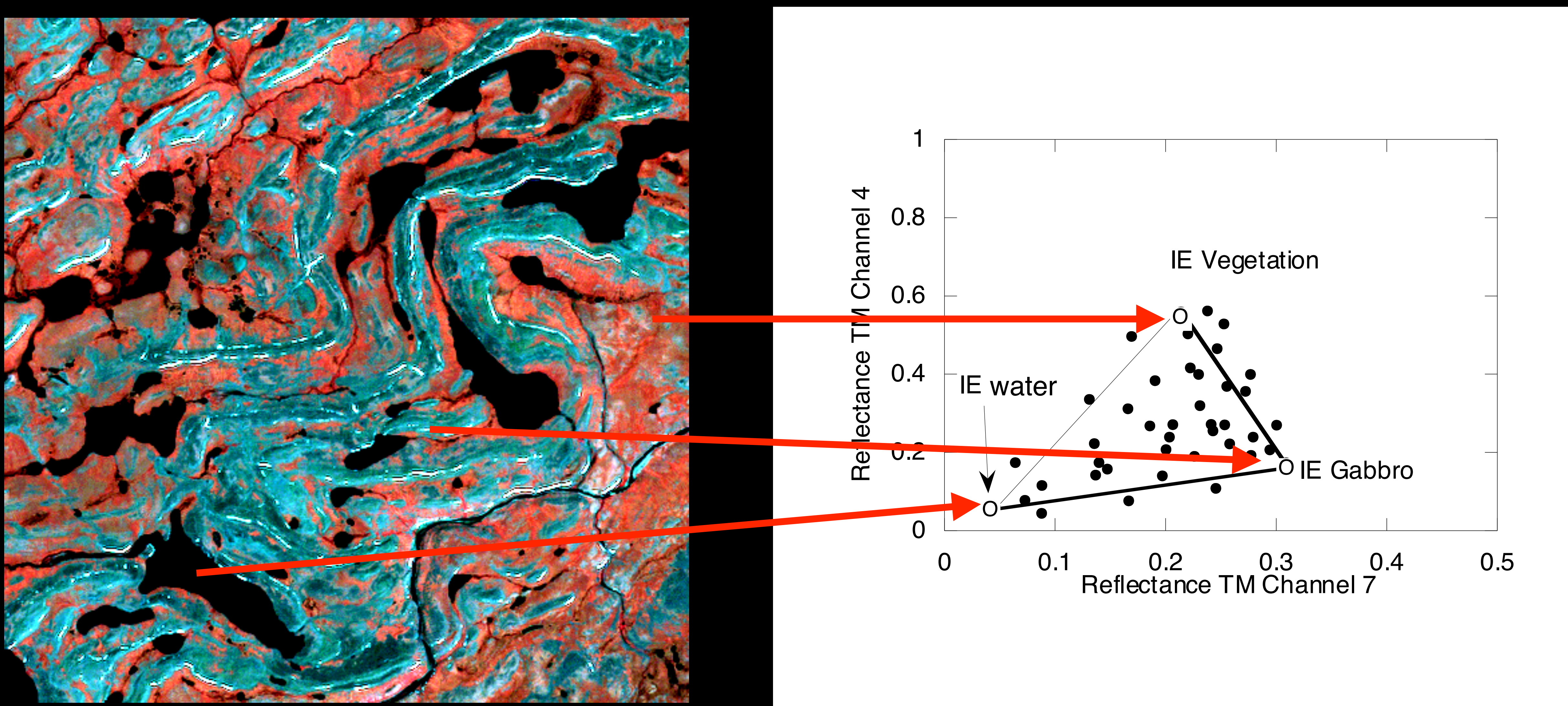


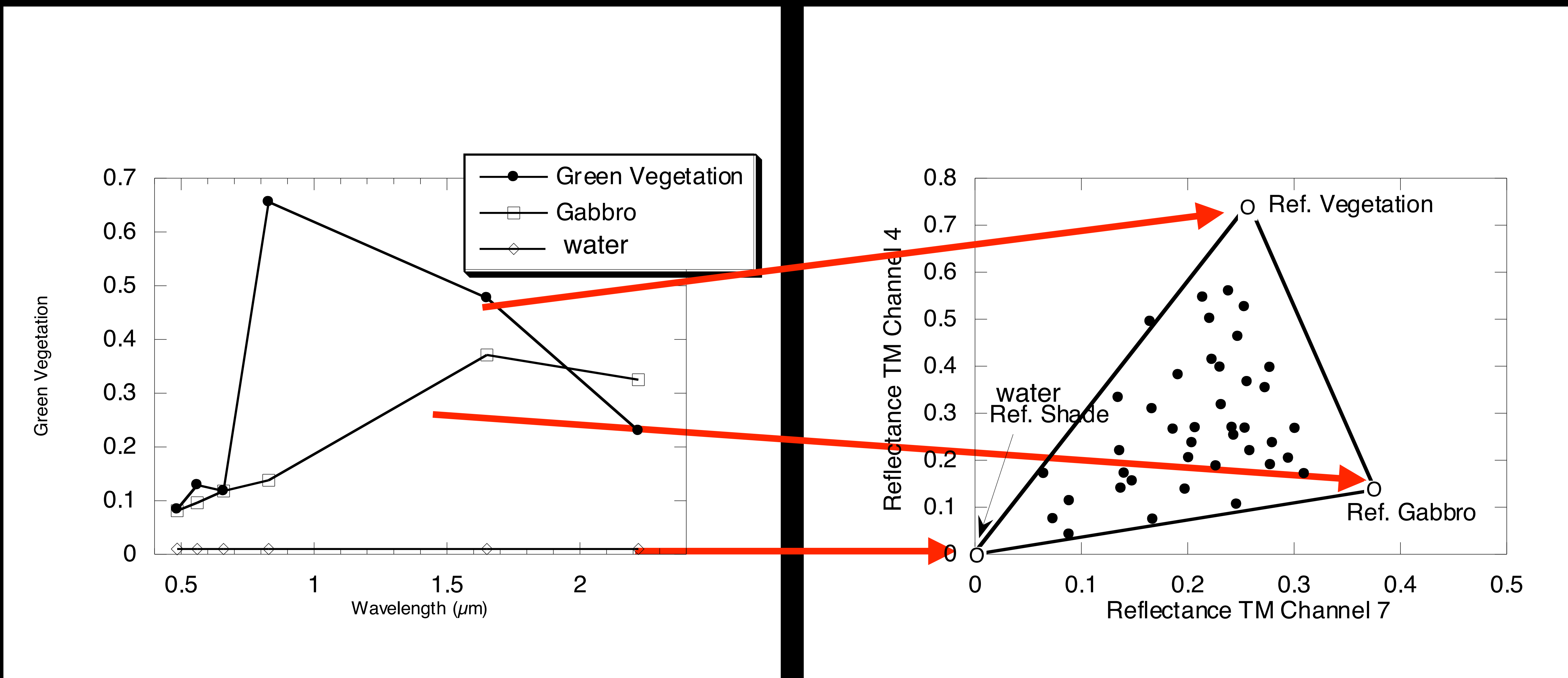
Image Endmembers

Find the endmembers in the image

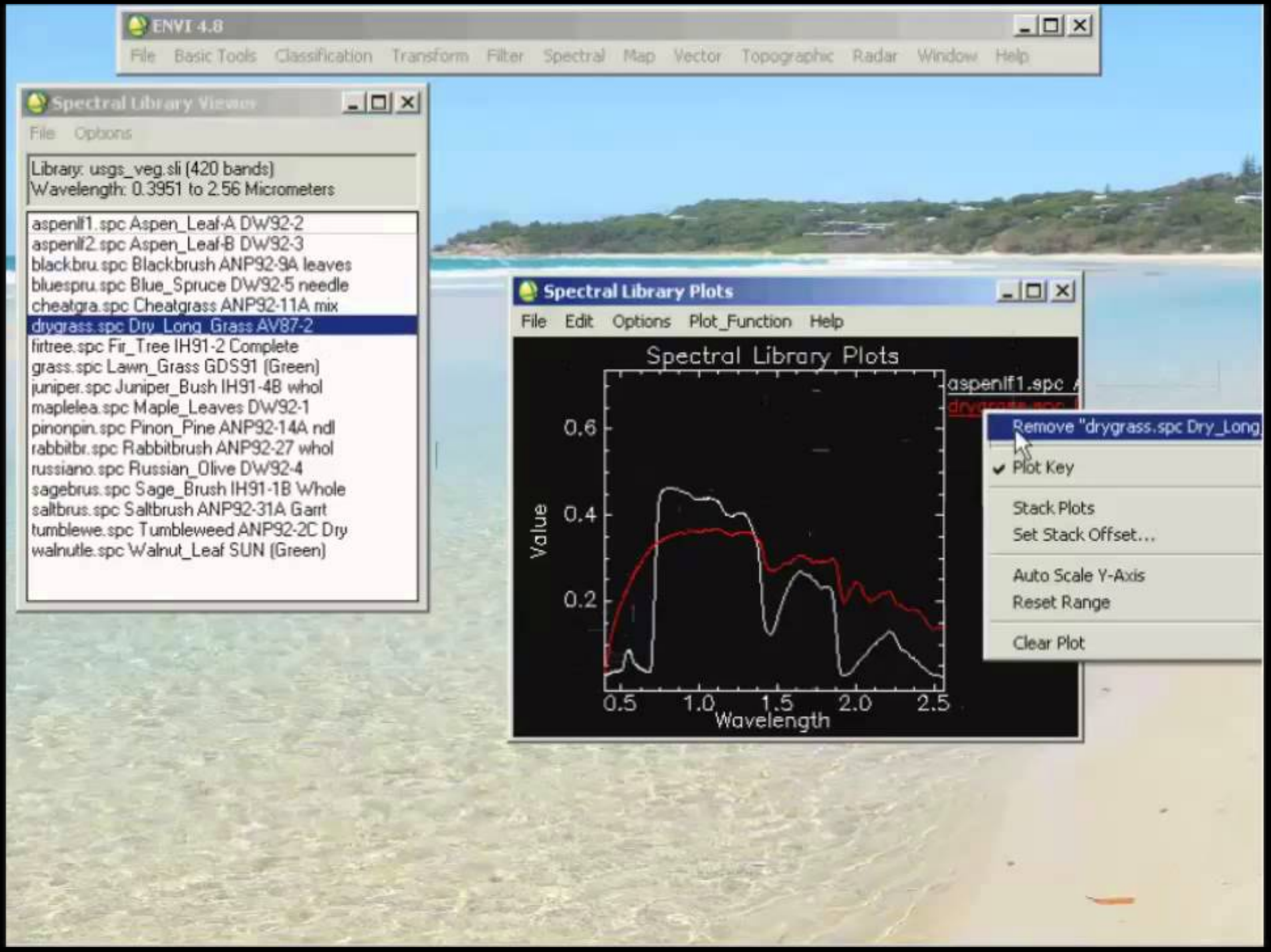


Library Endmembers

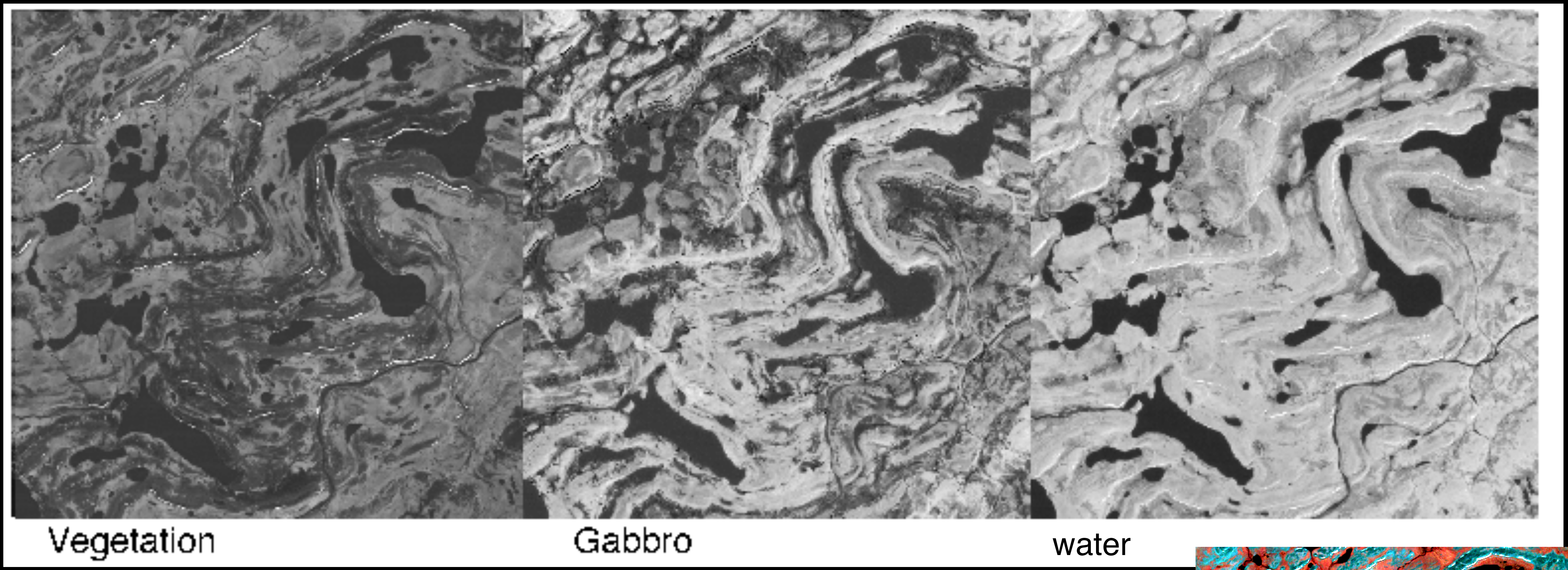
Get the pure endmember spectra from spectra library.
How to build a spectra library???

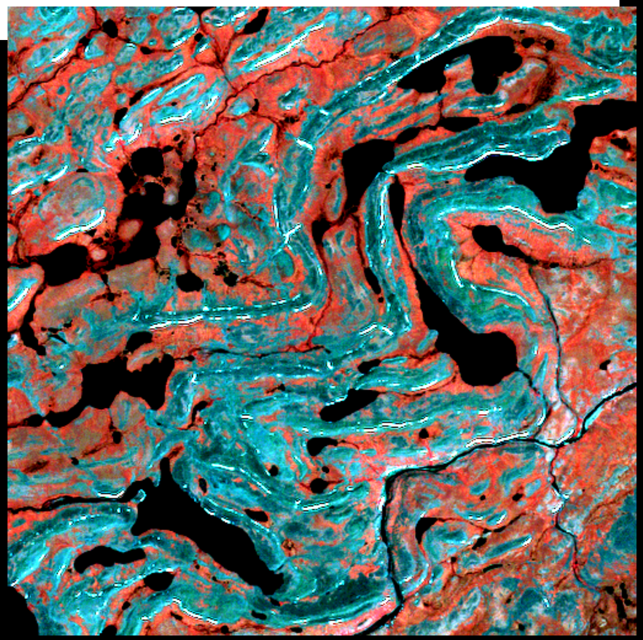


Field measurements of spectra

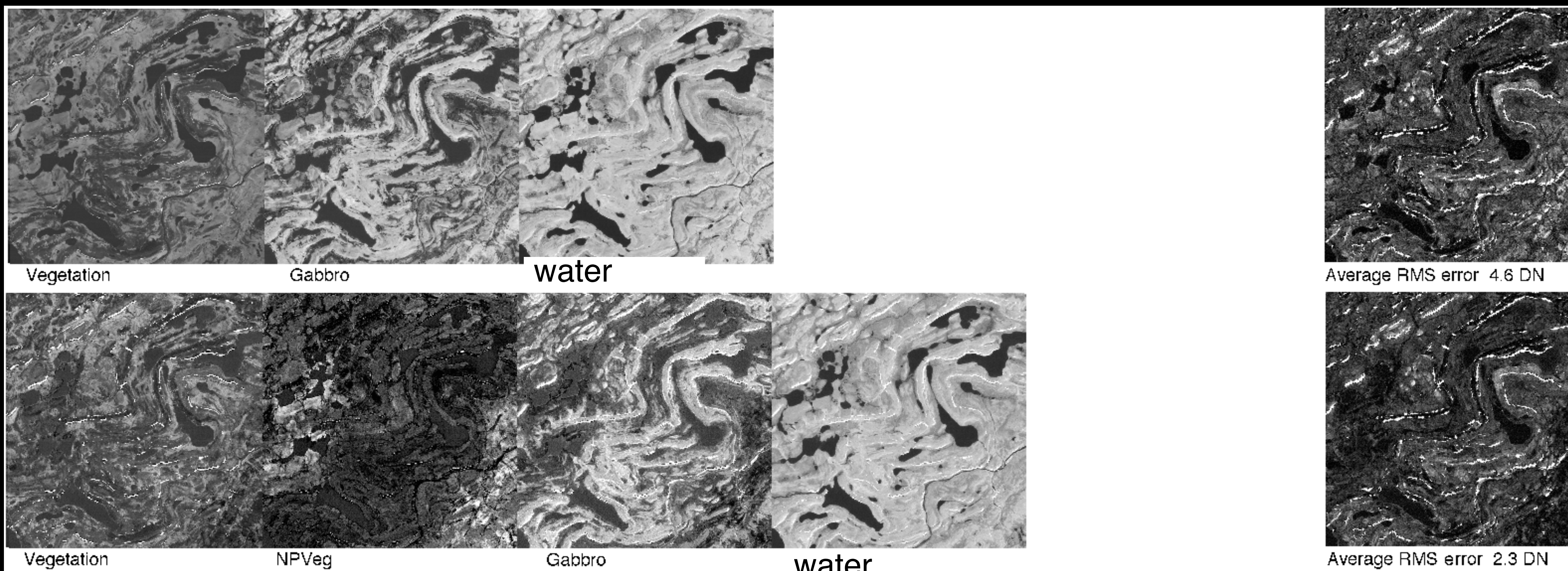


The result is a map of the percentage of endmembers in each pixel





Adding endmembers can reduce the error



$$\rho_\lambda = F_1\rho_{\lambda,1} + F_2\rho_{\lambda,2} + ... + F_N\rho_{\lambda,N} + E_\lambda$$

$$RMSE = \sqrt{\sum_{\lambda=1}^{N} \frac{(E_\lambda)^2}{N}}$$

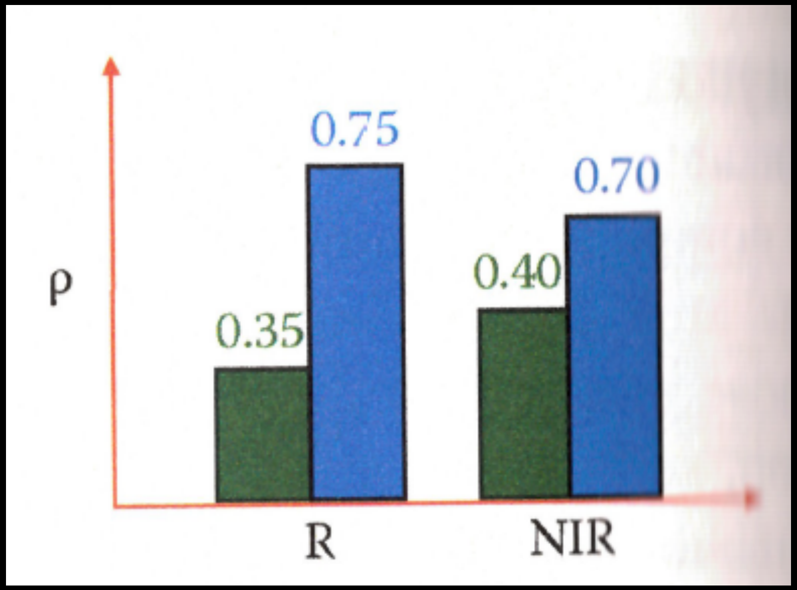
A two-endmember example

0.43	0.51	0.55
0.47	0.55	0.59
0.51	0.63	0.80

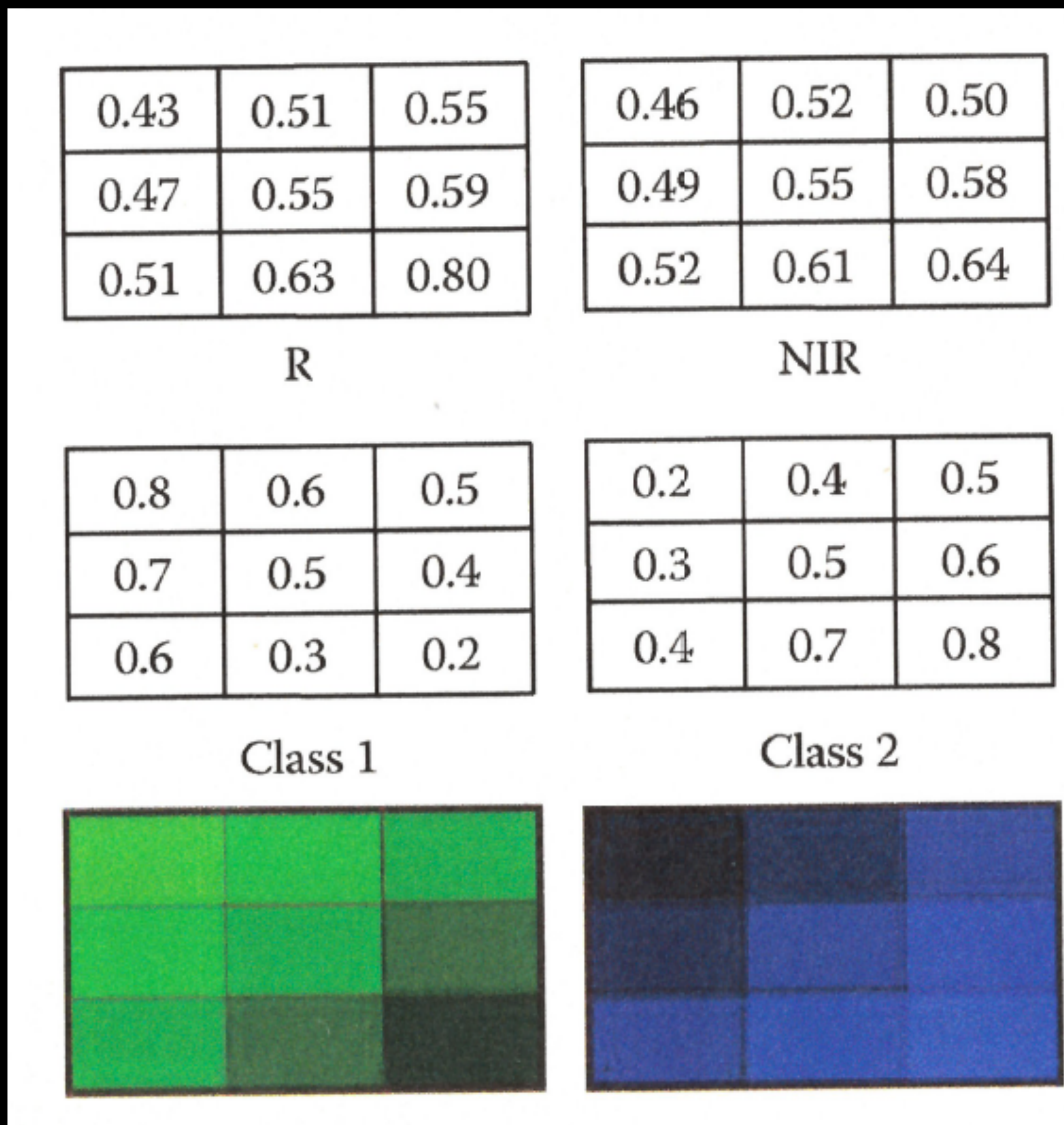
R

0.46	0.52	0.50
0.49	0.55	0.58
0.52	0.61	0.64

NIR



A two-endmember example



0.43	0.51	0.55
0.47	0.55	0.59
0.51	0.63	0.80

R

0.46	0.52	0.50
0.49	0.55	0.58
0.52	0.61	0.64

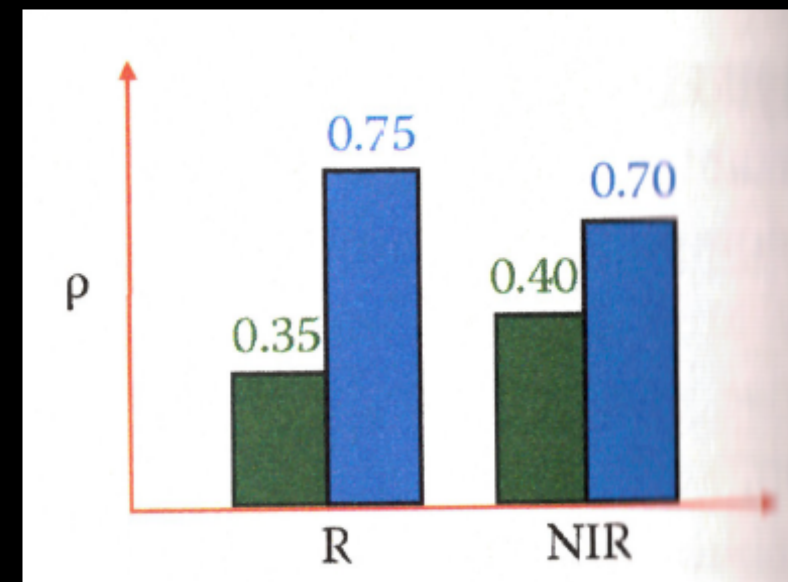
NIR

0.8	0.6	0.5
0.7	0.5	0.4
0.6	0.3	0.2

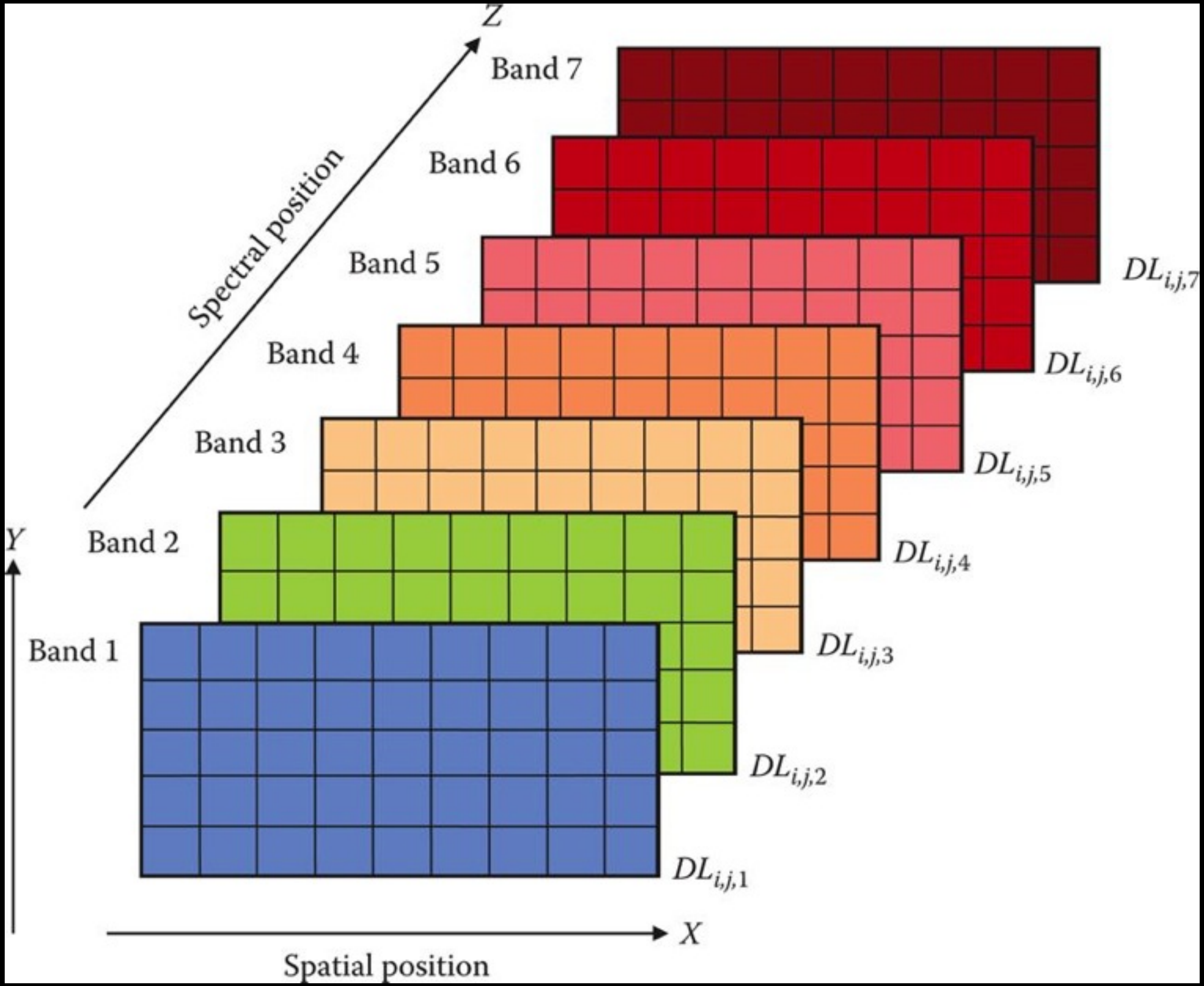
Class 1

0.2	0.4	0.5
0.3	0.5	0.6
0.4	0.7	0.8

Class 2

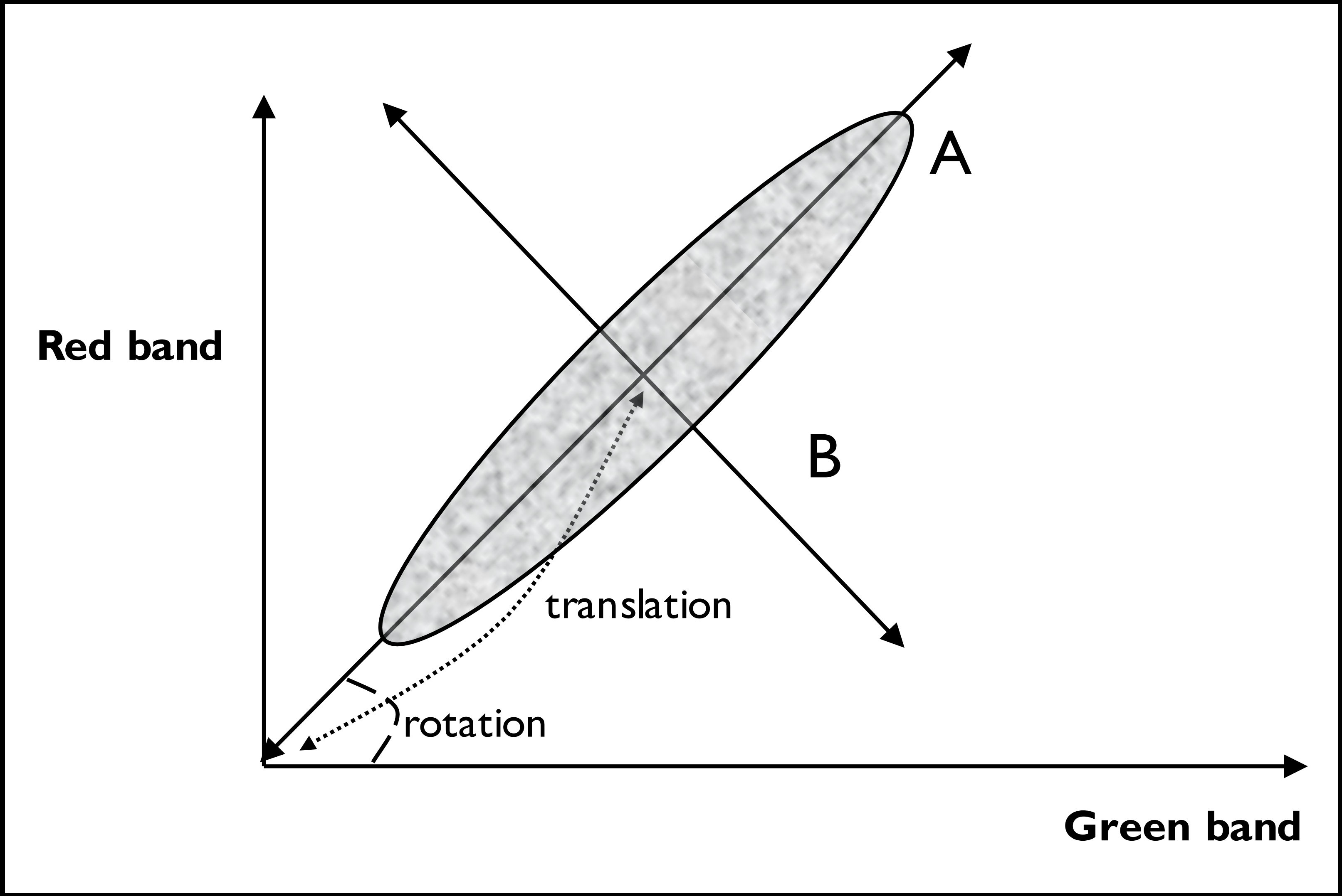


Questions



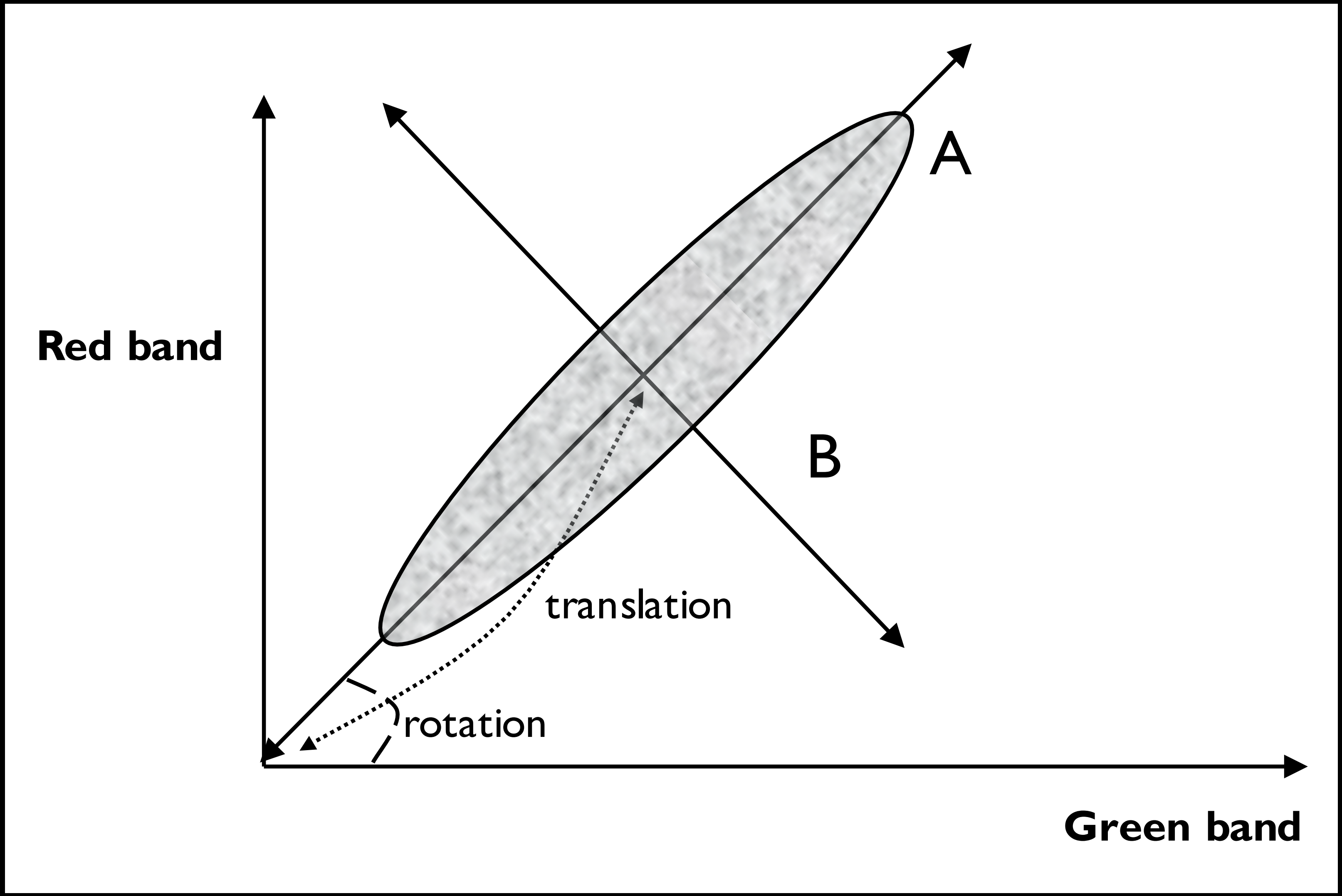
- A lot of redundant/useful information. Big data: extremely large data sets that may be analyzed computationally to reveal patterns, trends, and associations
- How to extract useful information from remote sensing images?

Principal Component Analysis (PCA)



- PCA: characterize a group of variables into a new smaller set, without losing a significant amount of original information.
- Create a new set of axes, and one axis explains the majority of the variations in the dataset.
- http://setosa.io/ev/principal-component-analysis/

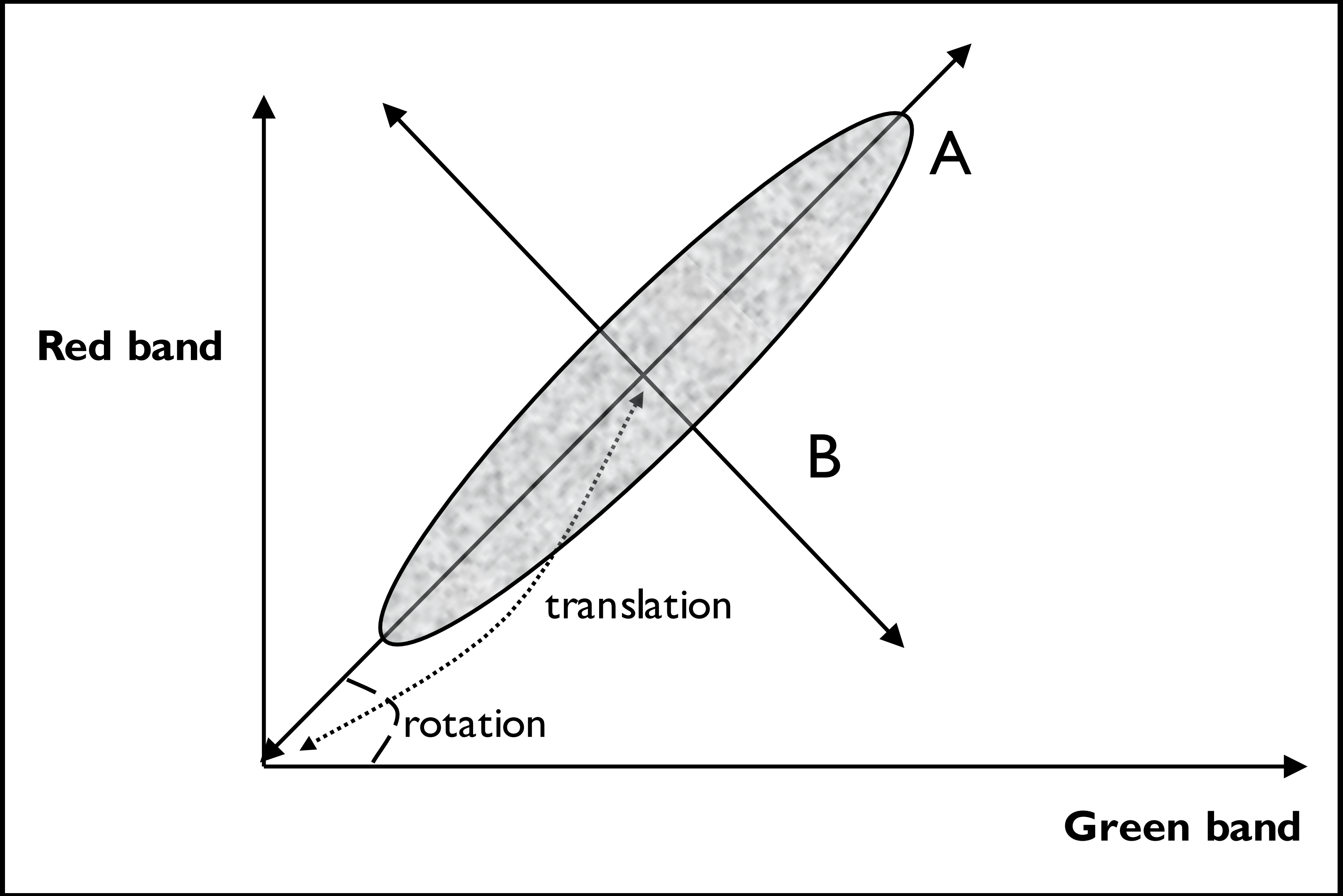
PCA, how to do it mathematically?



$$PC_1 = a_{1i}DN_i + a_{1k}DN_k$$

- PC_1: The new principal component on axis A;
- DN_i, DN_k: Digital numbers (or reflectance) of bands.

PCA, how to do it mathematically?



$$PC_j = \sum_{i=1,p} a_{i,j} DN_i + R_j$$

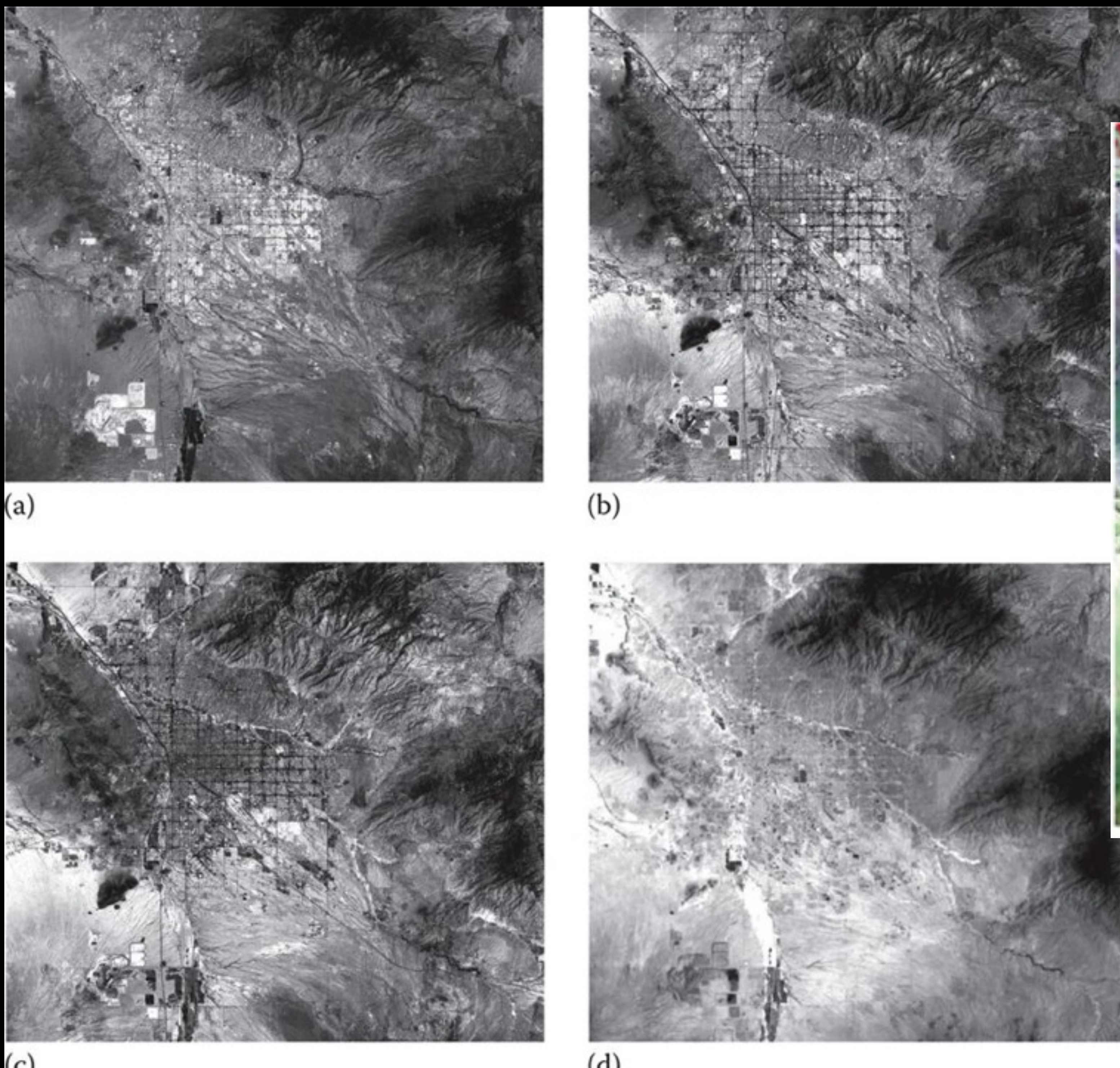
Principal component

coefficient

Digital number or reflectance

A constant

An example (Tucson)



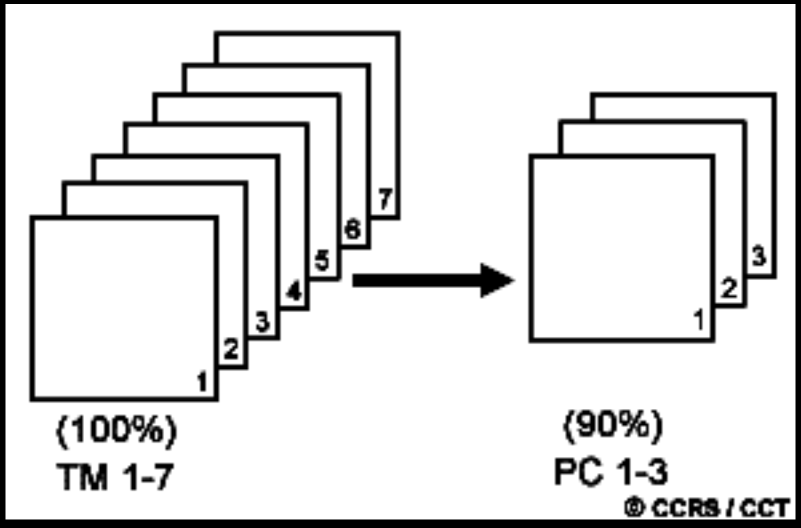
Eigenvector Matrix

	B	G	R	NIR	SWIR1	SWIR2	
	B1	B2	B3	B4	B5	B7	Variance (%)
CP1	0.552	0.188	0.465	0.320	0.380	0.444	85.04
CP2	0.285	–0.017	–0.546	0.503	0.385	–0.468	11.65
CP3	0.250	–0.847	–0.252	–0.033	–0.063	0.389	2.14

- PC 1: Looks like a weighted-average, and tells the overall brightness of the scene.
- How about PC 2 or 3?

Results of PCA

- The caveat of PCA: the interpretation of each principle component is scene-dependent



Kauth-Thomas Tasseled Cap Trasformation

- First developed by Kauth and Thomas (1976)

$$B = 0.332 \times MSS1 + 0.603 \times MSS2 + 0.675 \times MSS3 + 0.332 \times MSS4$$

$$G = -0.283 \times MSS1 - 0.660 \times MSS2 + 0.577 \times MSS3 + 0.388 \times MSS4$$

$$Y = -0.899 \times MSS1 + 0.428 \times MSS2 + 0.076 \times MSS3 - 0.041 \times MSS4$$

$$N = -0.016 \times MSS1 + 0.131 \times MSS2 - 0.452 \times MSS3 + 0.882 \times MSS4$$

- Later improved by Crist et al. (1986) with Landsat TM

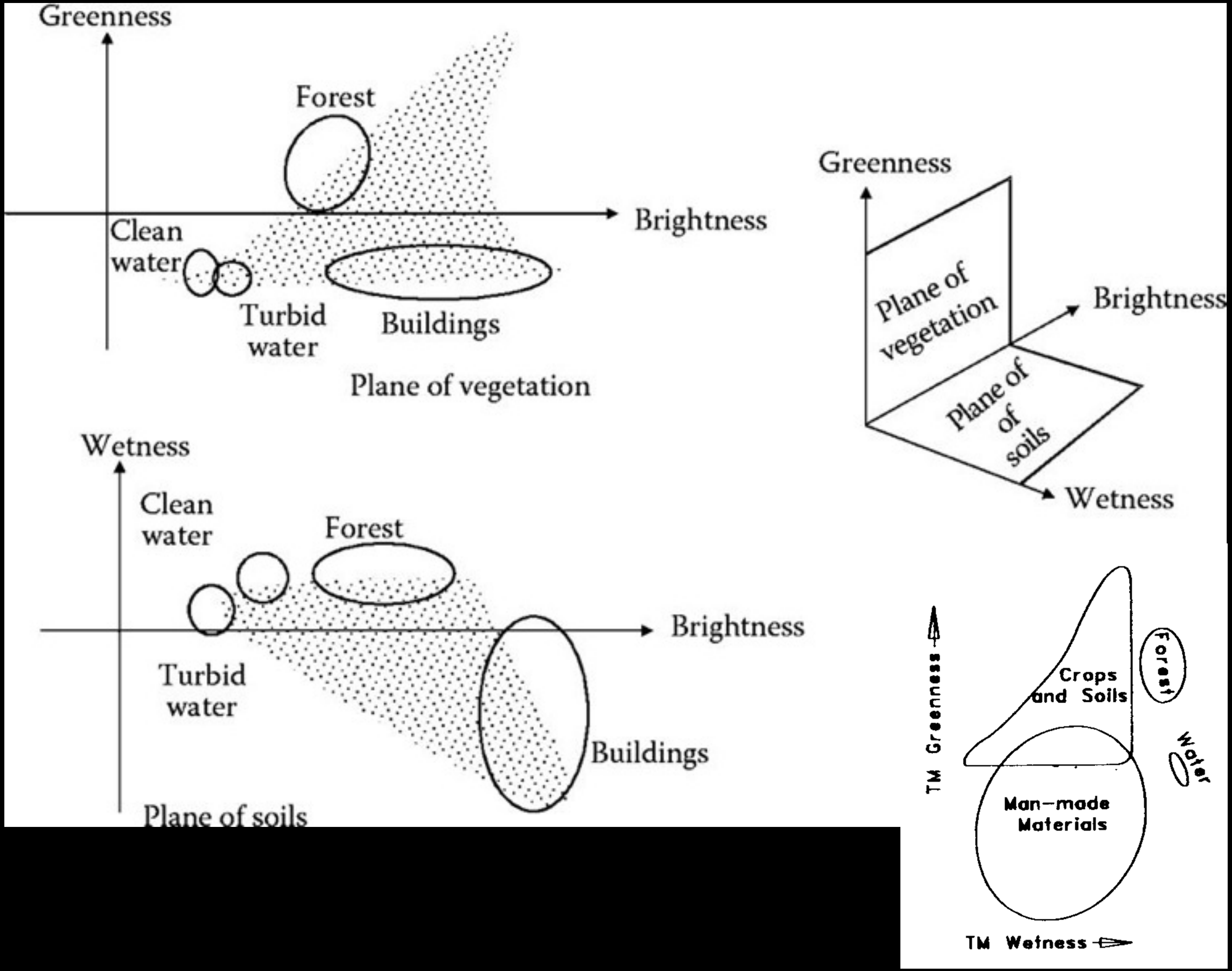
$$\begin{aligned} B = {} & 0.2909\,TM1 + 0.2493\,TM2 + 0.4806\,TM3 + \\ & 0.5568\,TM4 + 0.4438\,TM5 + 0.1706\,TM7 \end{aligned}$$

$$\begin{aligned} G = {} & -0.2728\,TM1 - 0.2174\,TM2 - 0.5508\,TM3 + \\ & 0.7221\,TM4 + 0.0733\,TM5 - 0.1648\,TM7 \end{aligned}$$

$$\begin{aligned} W = {} & 0.1446\,TM1 + 0.1761\,TM2 + 0.3322\,TM3 + \\ & 0.3396\,TM4 - 0.6210\,TM5 - 0.4186\,TM7\,. \end{aligned}$$

Kauth-Thomas Tasseled Cap Trasformation

- Physical meanings of each PC can be interpreted

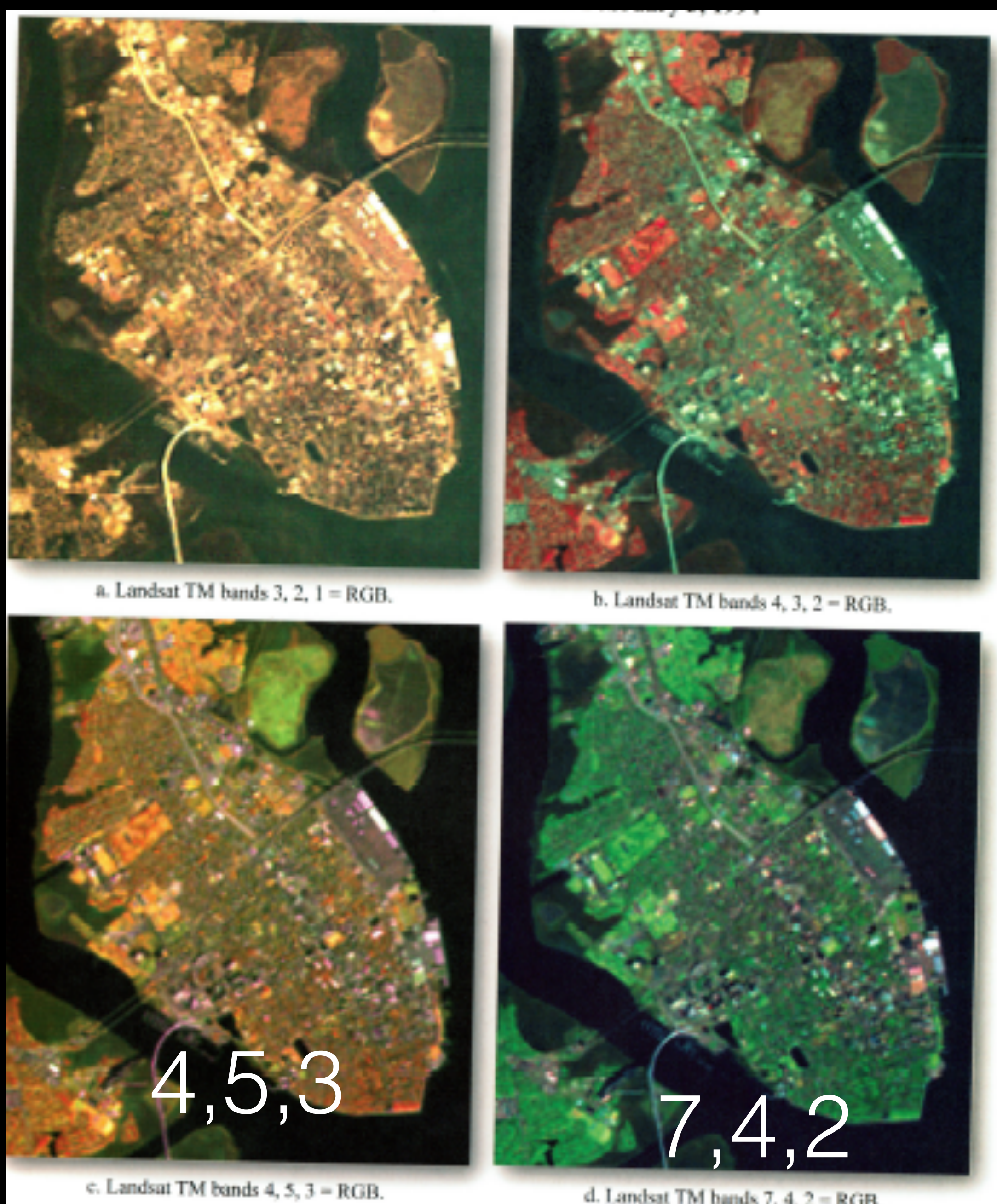


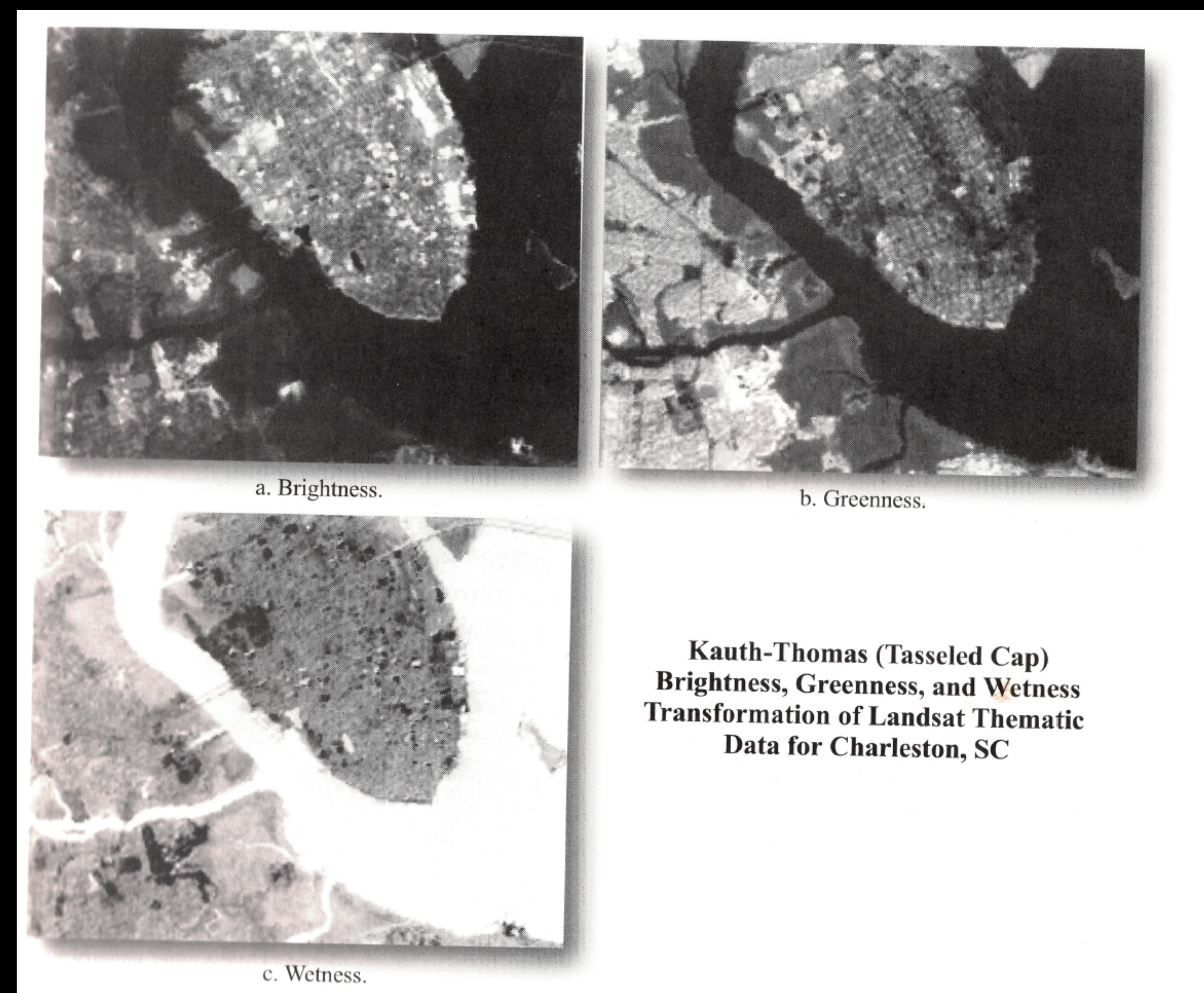
- 3 planes: 1) Vegetation; 2) Soils; 3) Transition

Kauth-Thomas Tasseled Cap Trasformation

- Physical meanings of each PC can be interpreted

3,2,1 4,3,2





Landsat bands

https://landsat.usgs.gov/what-are-best-spectral-bands-use-my-study