Hyperspectral remote sensing

Theory Applications and Methods

August 23, 2010

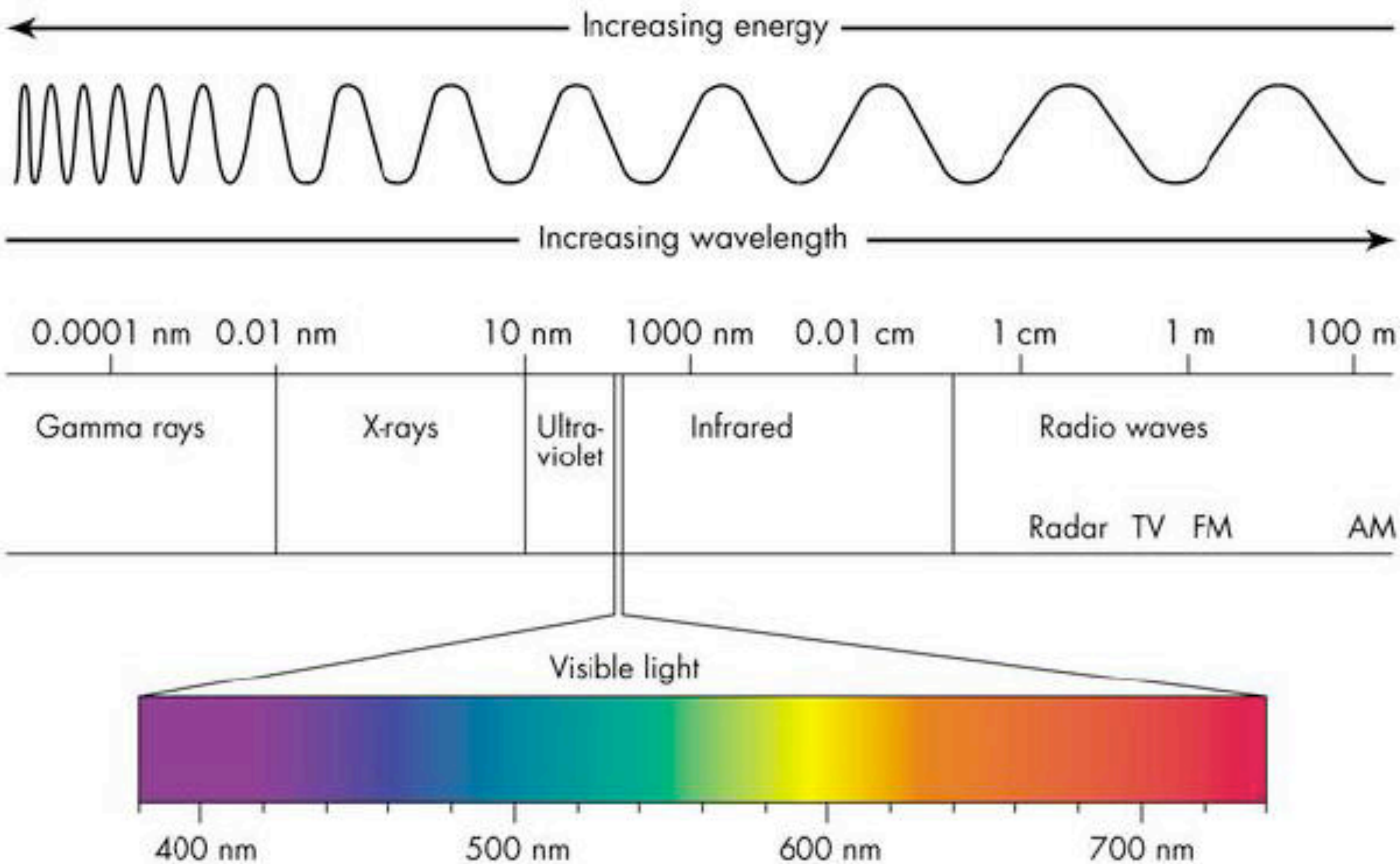
Domains of remote sensing

- Spatial domain
- Spectral domain
- Temporal domain
- Angular domain
- Polarization domain

Spectral domain

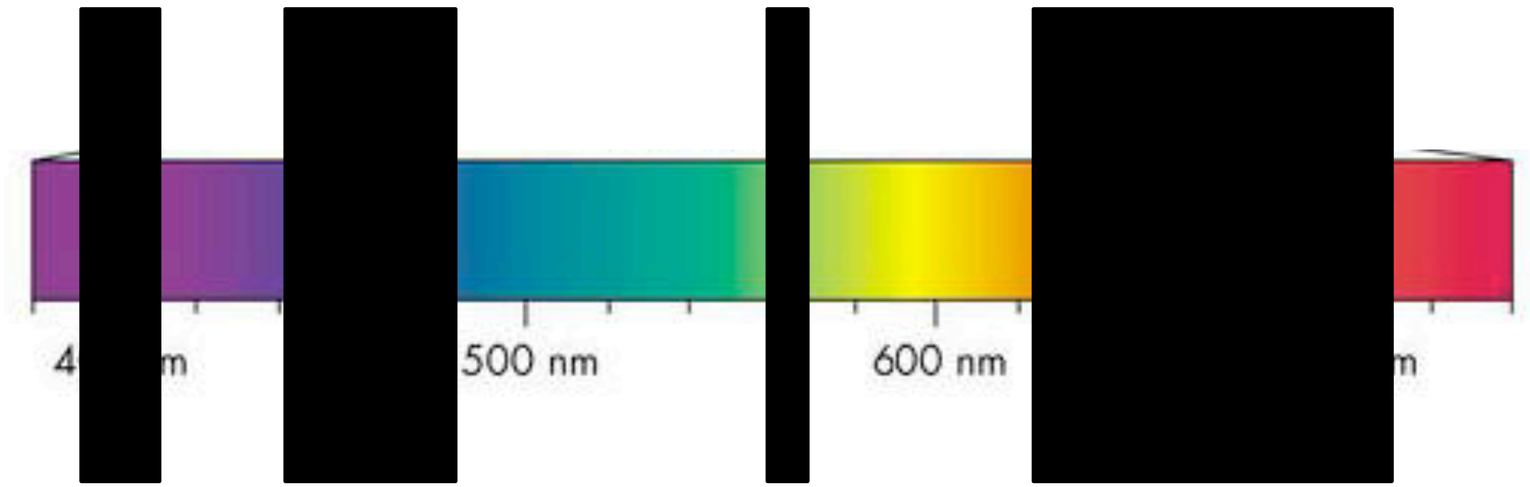
- Spectral location of “bands”
  - i.e. visible, IR, SWIR
- Band width
  - how wide are spectral positions?
- Number and frequency of bands
  - how many and at what frequency?

Electromagnetic Spectrum



The Sun produces a *continuous spectrum* of electromagnetic radiation ranging from very short, extremely high frequency gamma and cosmic waves to long, very low frequency radio waves

Spectral frequency
(how often do you sample the spectrum)

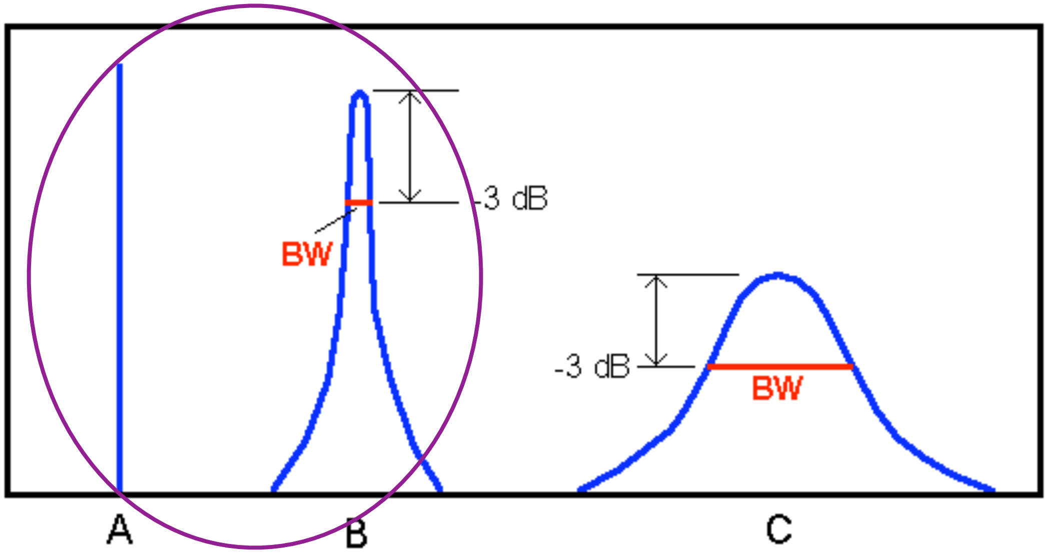


broadband example

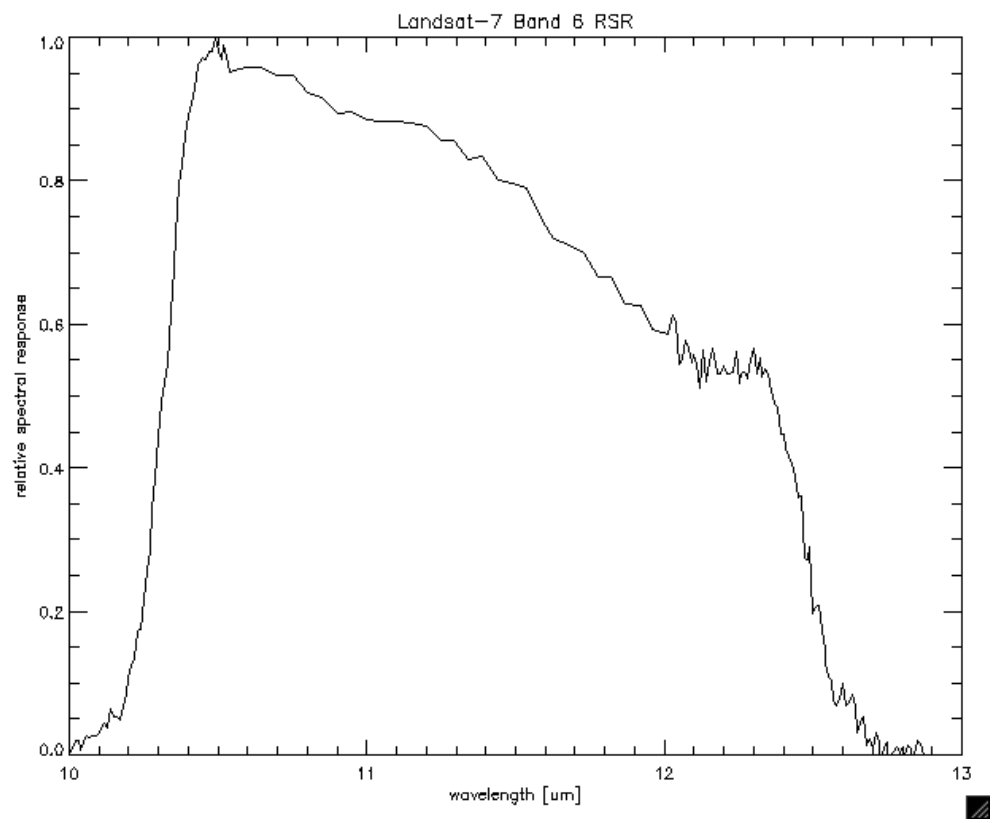
Spectral frequency
(how often do you sample the spectrum)

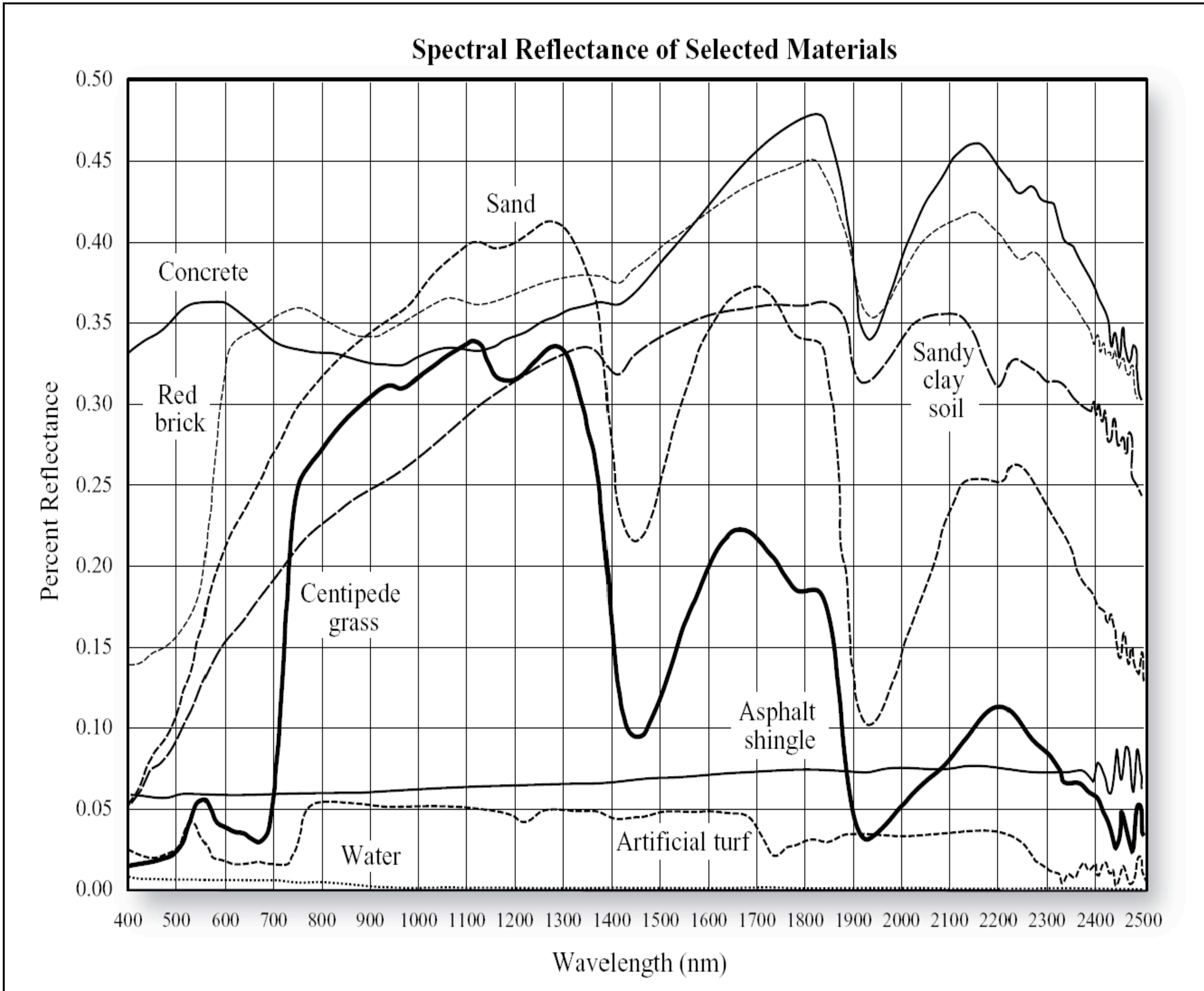
hyperspectral example
(hyper [many] - spectral)

Spectral bandwidth

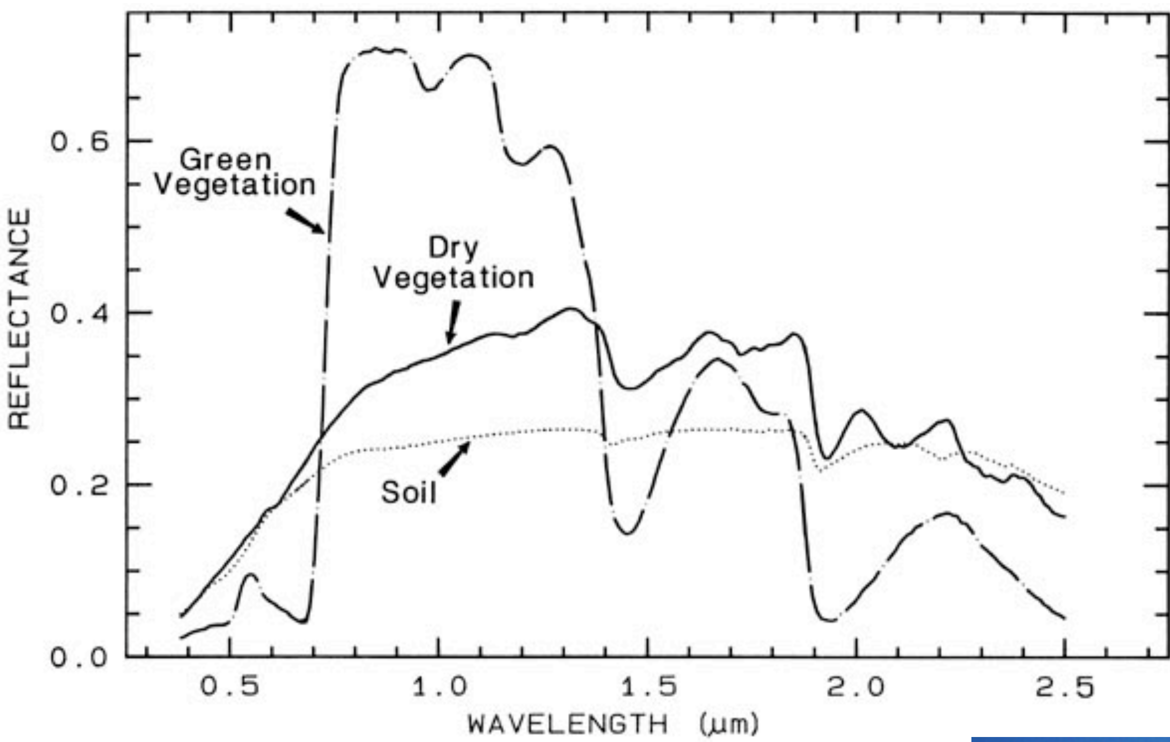


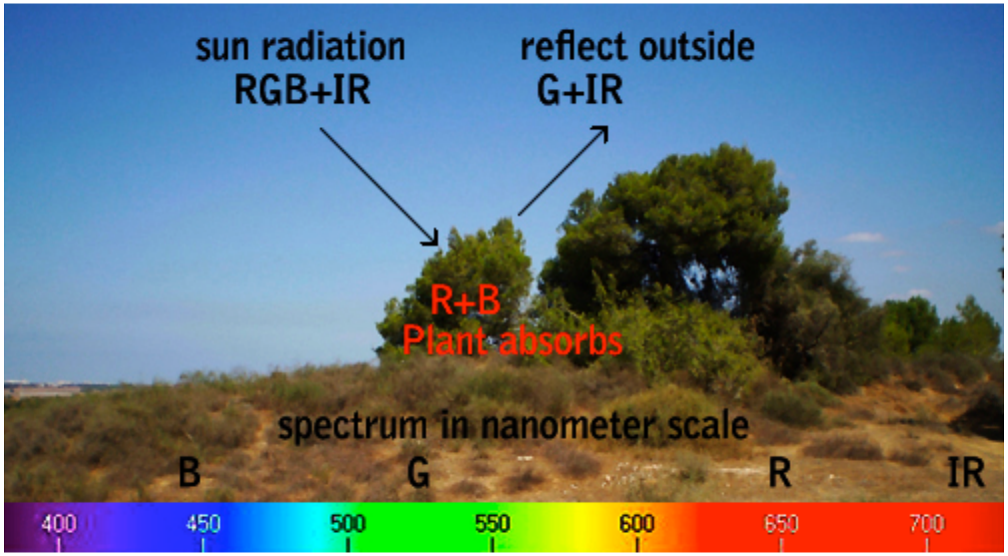
Landsat Band 6
spectral response



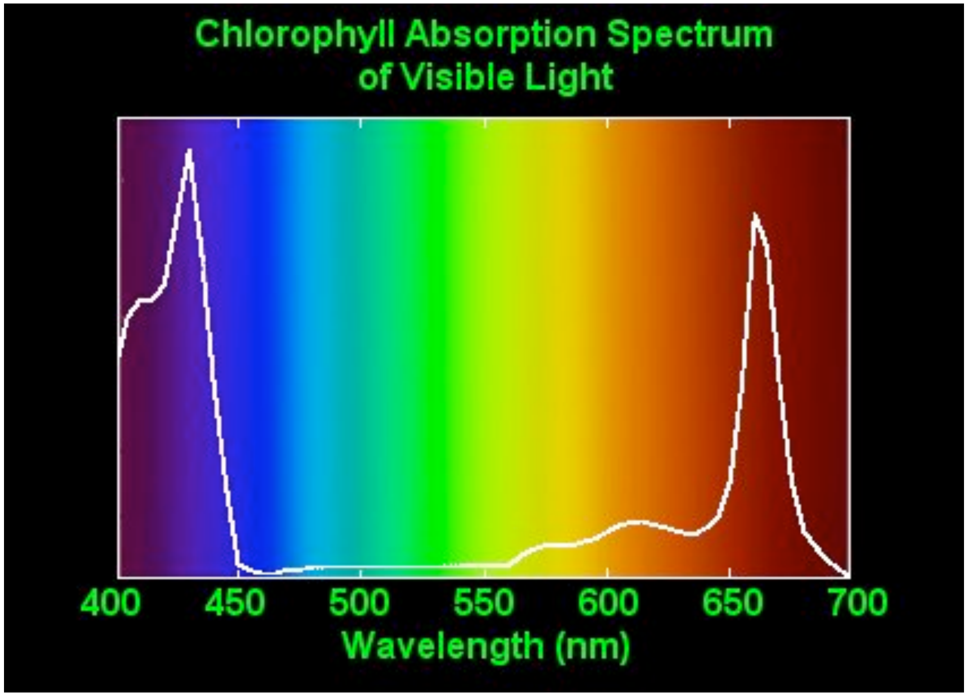

Spectral Reflectance of Selected Materials
Percent Reflectance
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
400
500
600
700
800
900
1000
1100
1200
1300
1400
1500
1600
1700
1800
1900
2000
2100
2200
2300
2400
2500
Wavelength (nm)
Sand
Concrete
Red brick
Centipede grass
Sandy clay soil
Asphalt shingle
Artificial turf
Water

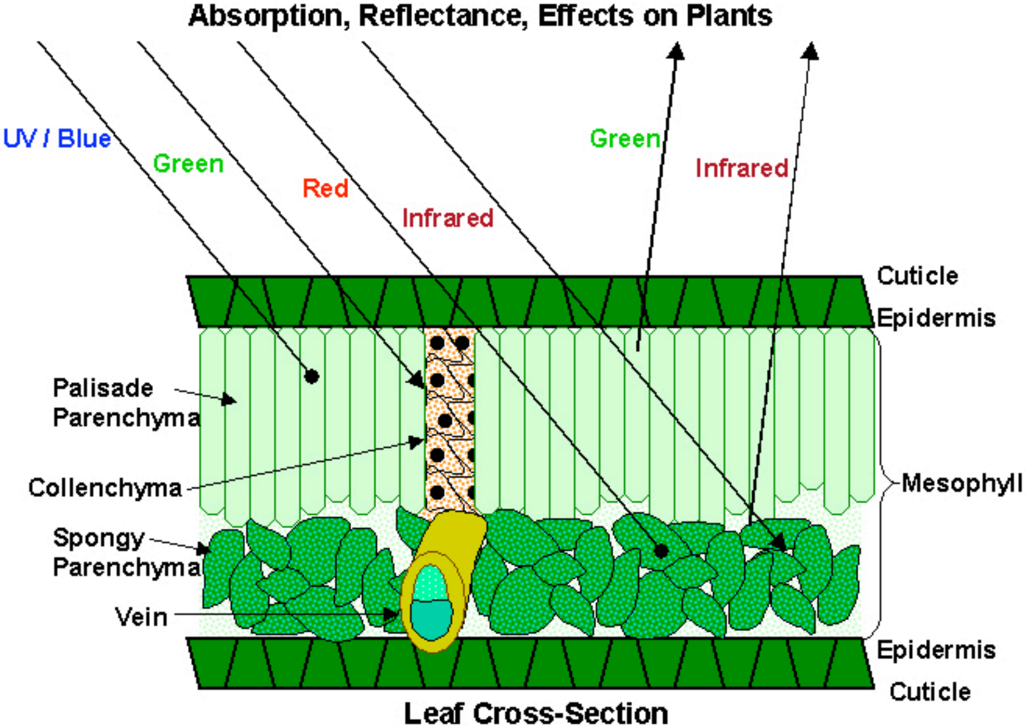
Dry vs. Green vegetation



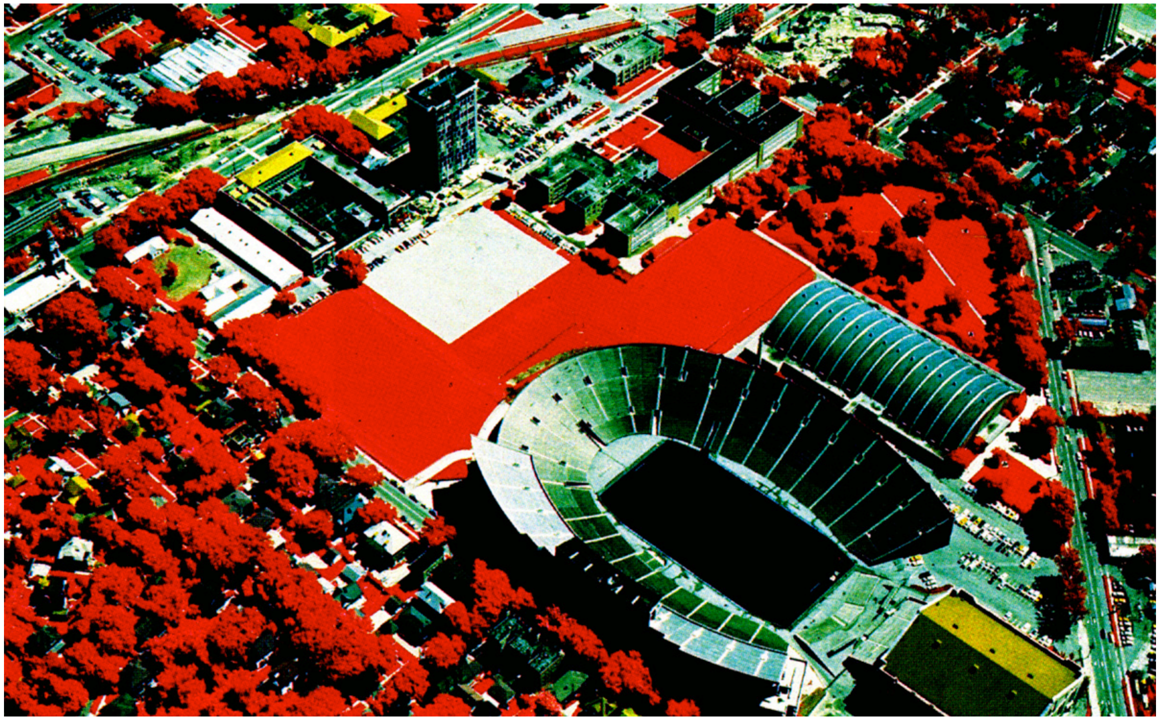


Leaf reflectance and absorption



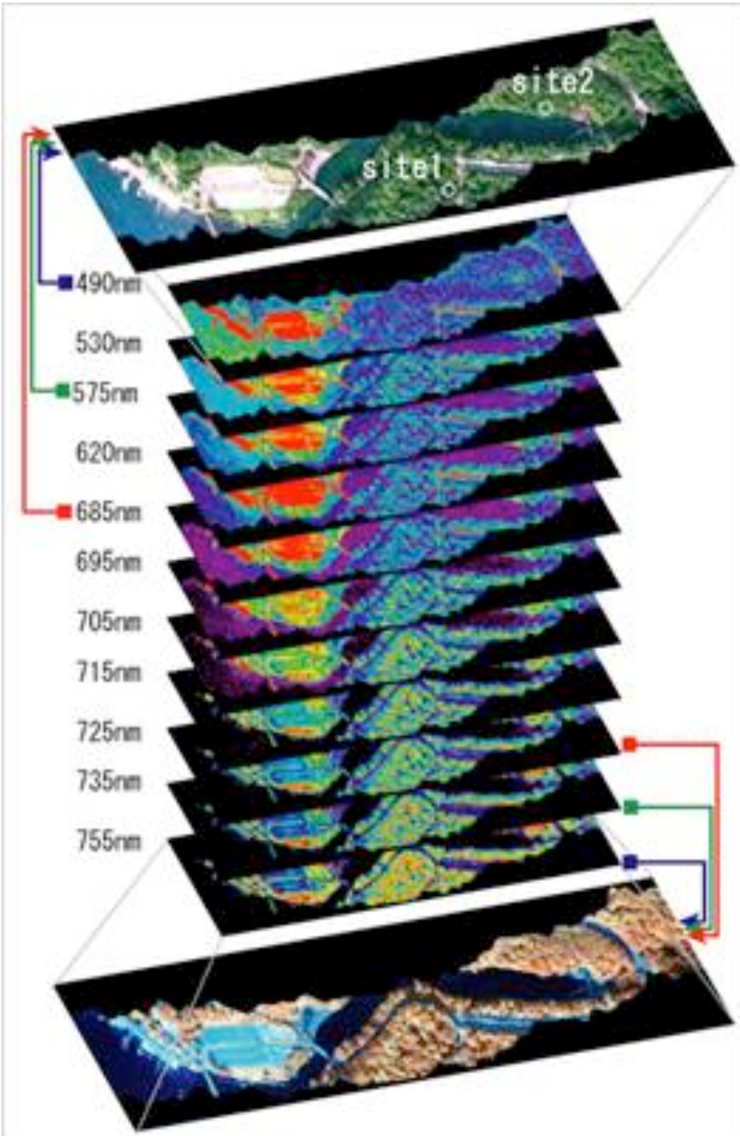


color aerial photo
visible spectrum



color aerial photo
NIR spectrum

Spectral frequency



hyperspectral cube

Imaging spectroscopy

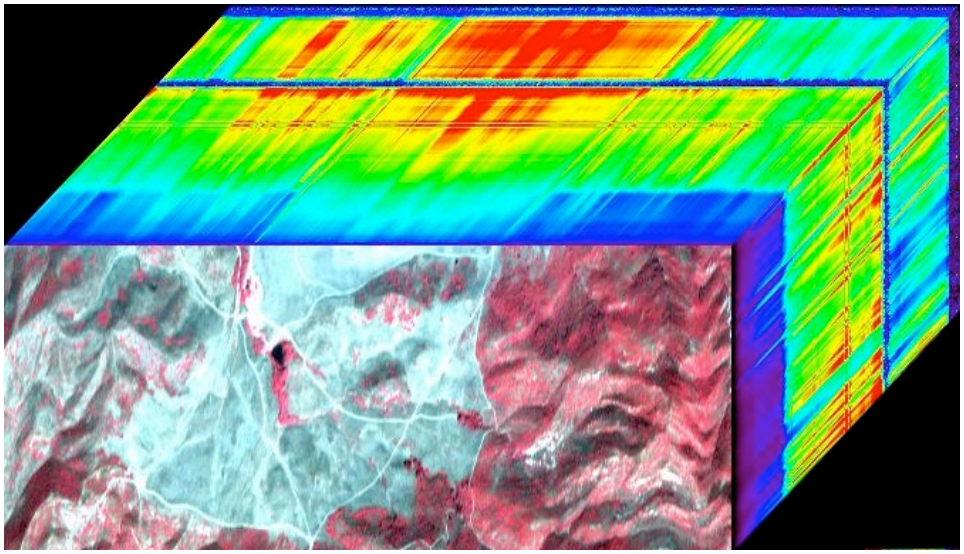
what is imaging spectroscopy?

- systems with **narrow spectral bands** used to obtain a *continuous spectrum* of electromagnetic radiation

- complete characterization of spectral properties

- more detail – reveals surface chemistry, physical properties and geometry

- new capabilities for analysis



- spectral libraries

Motivation

- Imaging spectrometry provides fundamental spectral information that is not accessible to broad band systems
- Imaging spectrometry provides fundamental measurements that add value to broad band systems
- Imaging spectrometry provides flexibility, enabling the simultaneous solution of numerous remote sensing problems

Courtesy of Dar Roberts
UCSB

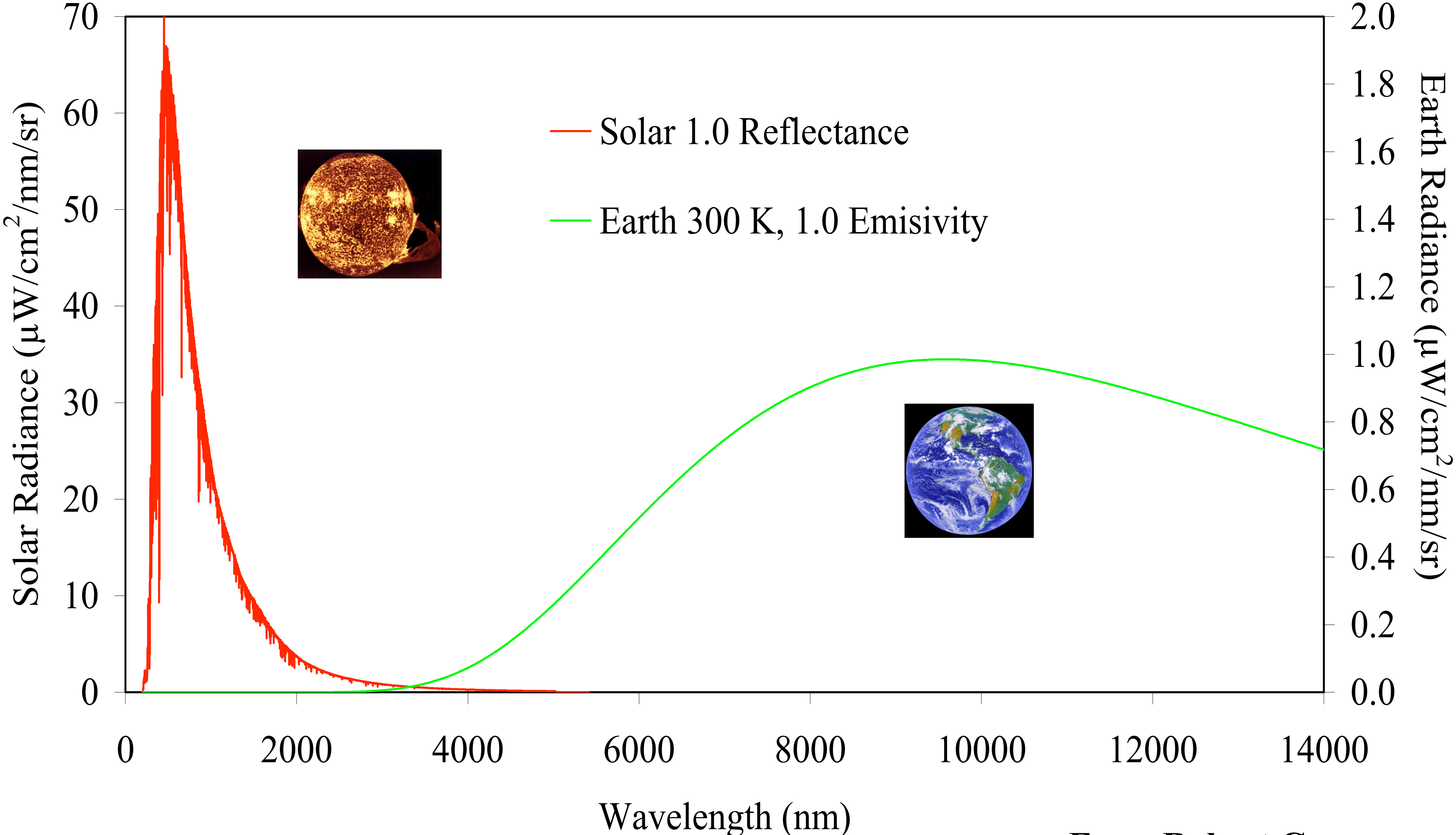
Applications

Atmospheres

- The atmosphere imposes its signature upon all remote sensing measurements
- The atmosphere must be characterized to solve for surface reflectance
- Various atmospheric constituents can be mapped using an imaging spectrometer

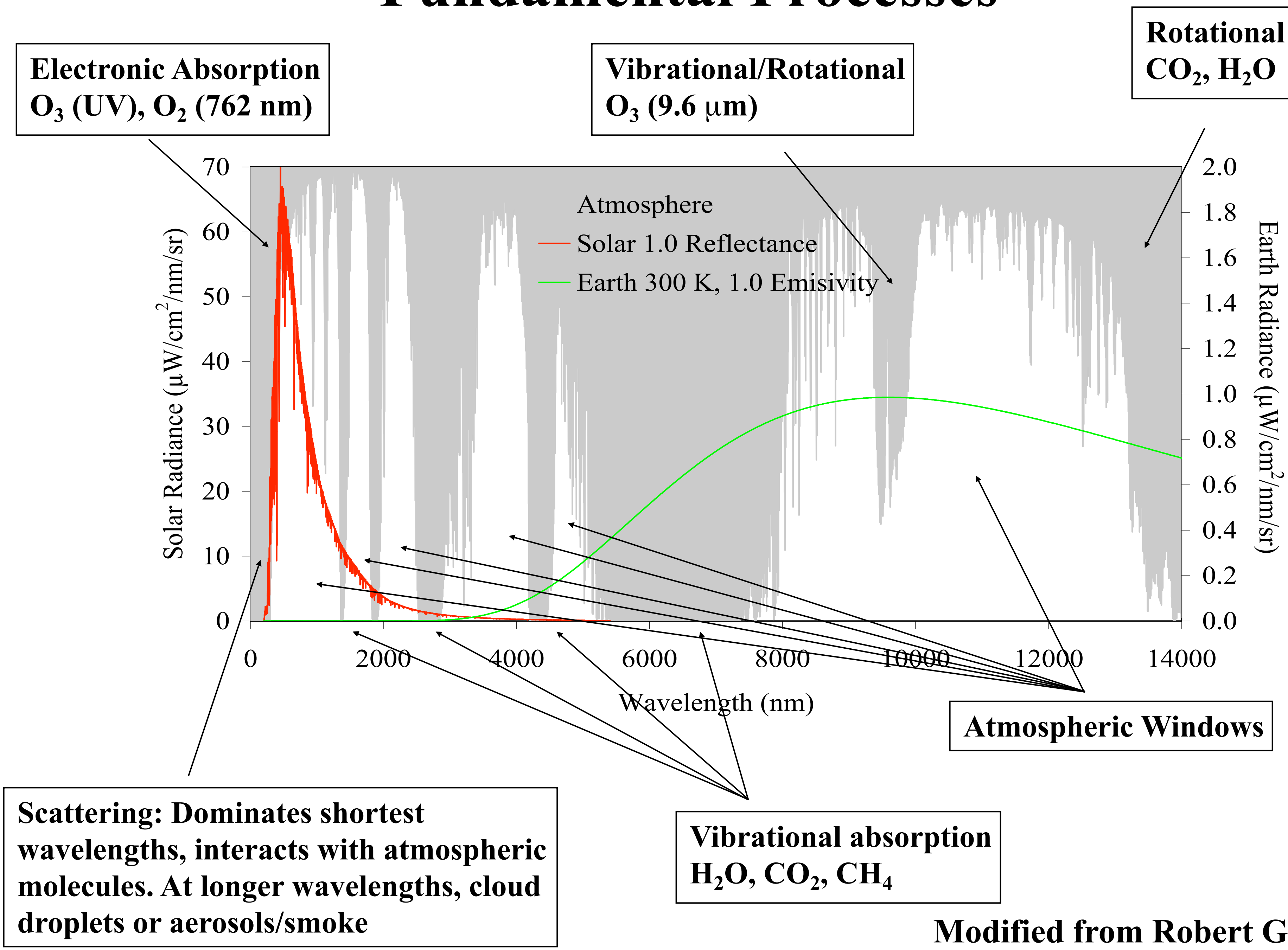
Courtesy of Dar Roberts
UCSB

Emission Spectra of the Sun and Earth with no Atmosphere



From Robert Green

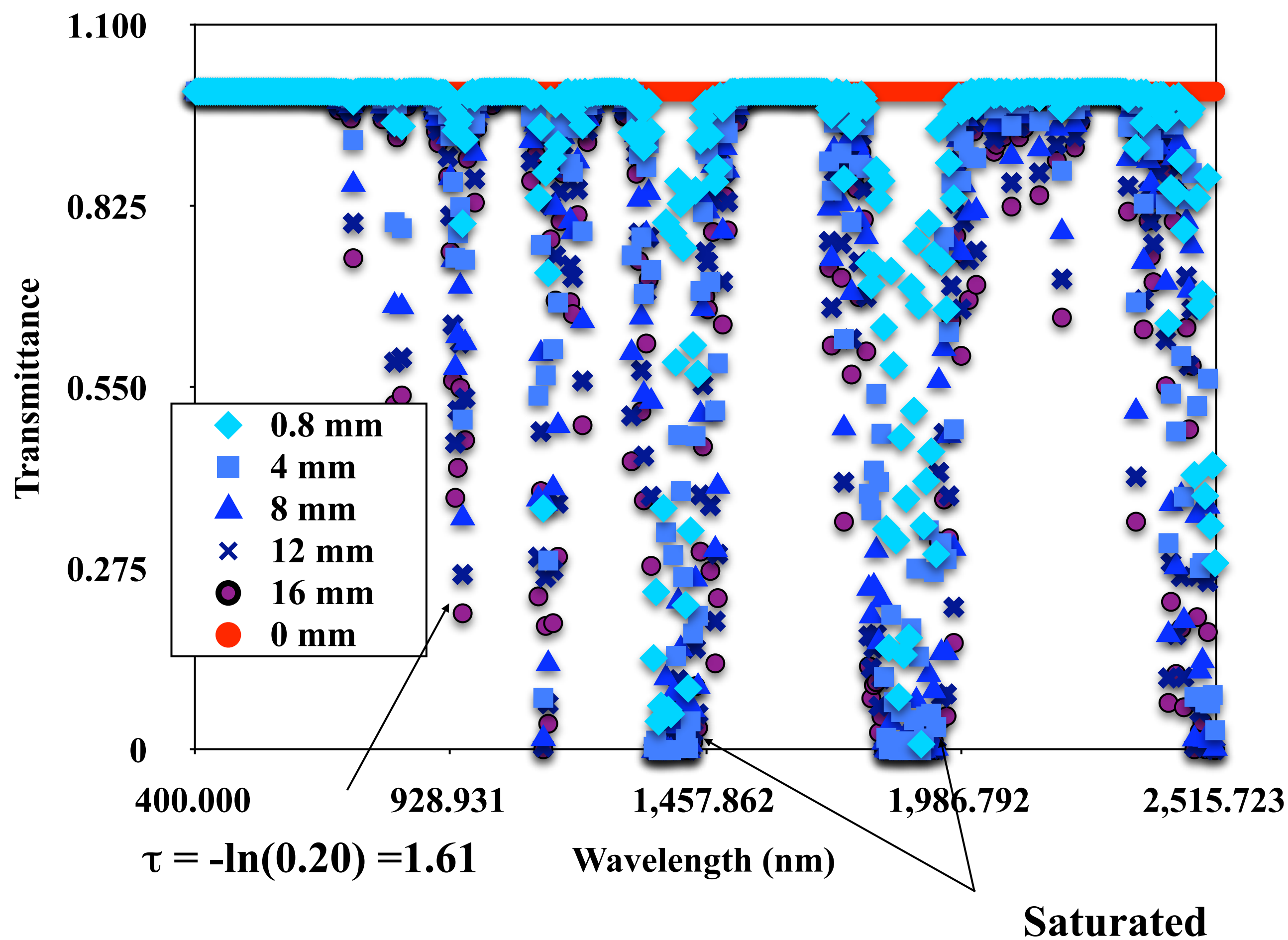
Fundamental Processes



Modified from Robert Green

Impact of Water Vapor

- Water vapor is unique in that it varies considerably over space and time



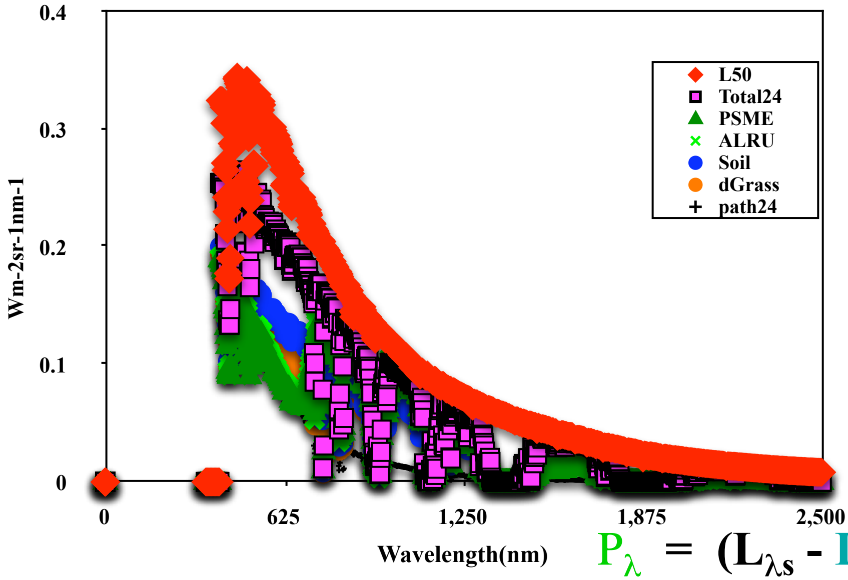
$\tau = -\ln(0.20) = 1.61$

Modtran: March 21, 100 km elev, 1 atm

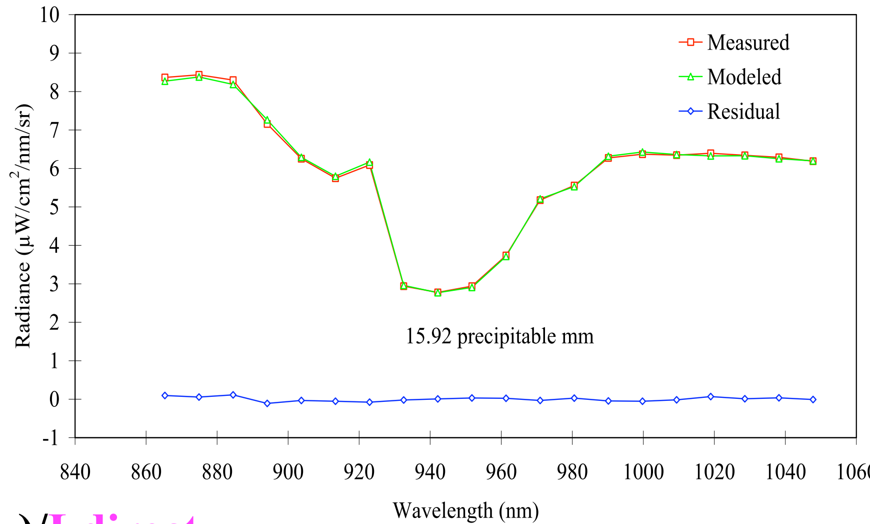
Courtesy of Dar Roberts
UCSB

Radiative Transfer Solution for Reflectance

Models and Measurements

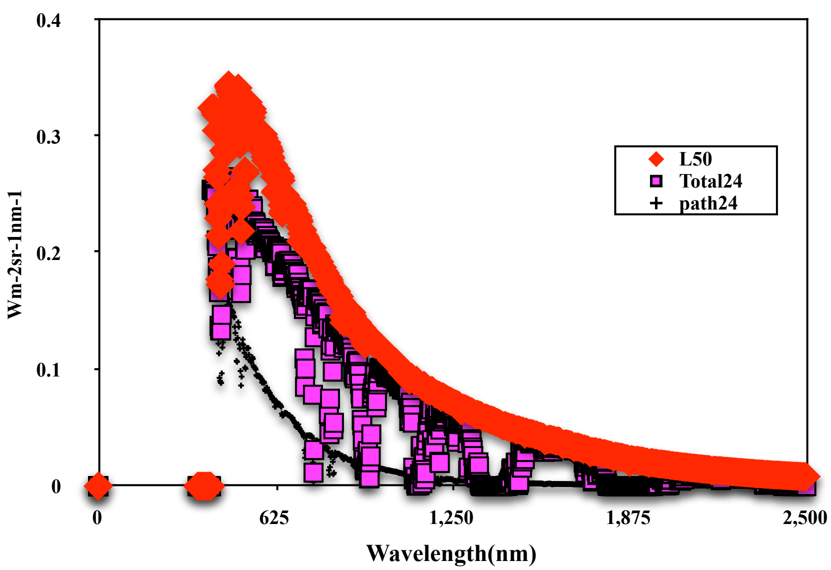


Spectral Fit in Water Vapor Band

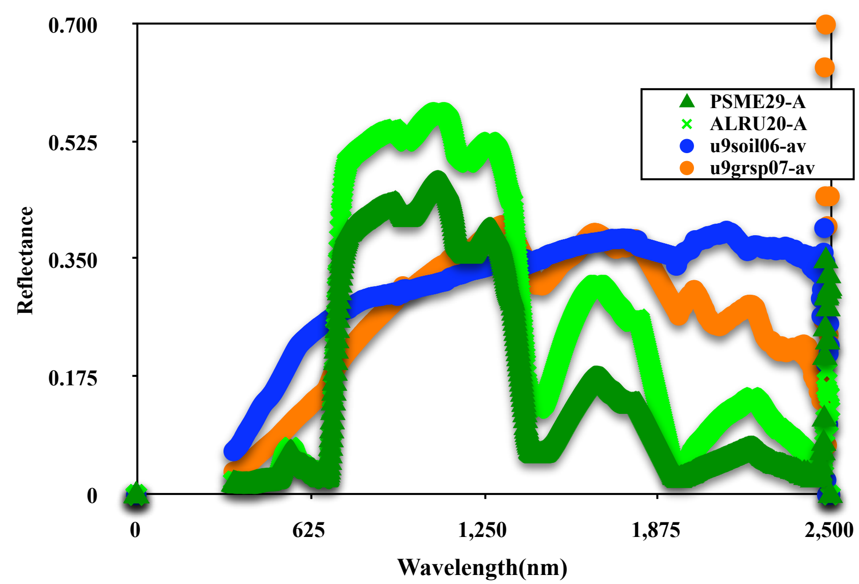


$$P_\lambda = (L_{\lambda s} - Lpath_\lambda)/Ldirect_\lambda$$

Modeled Radiance



Retrieved Reflectance



Courtesy of Dar Roberts
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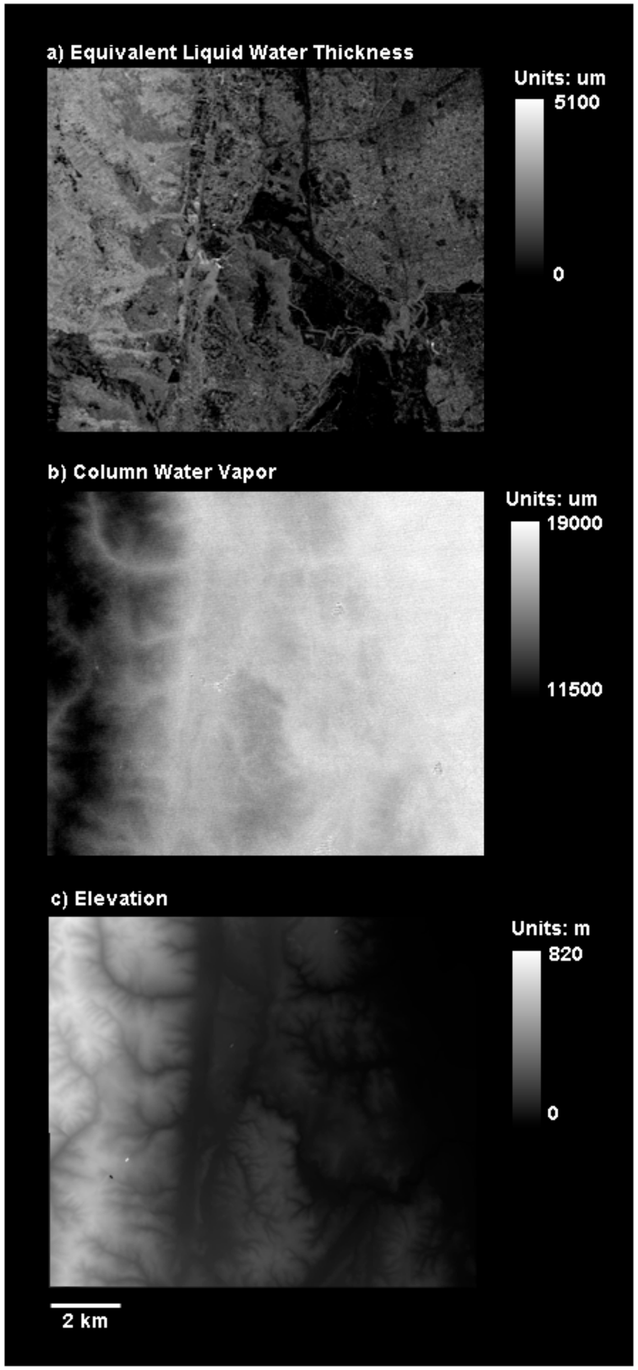
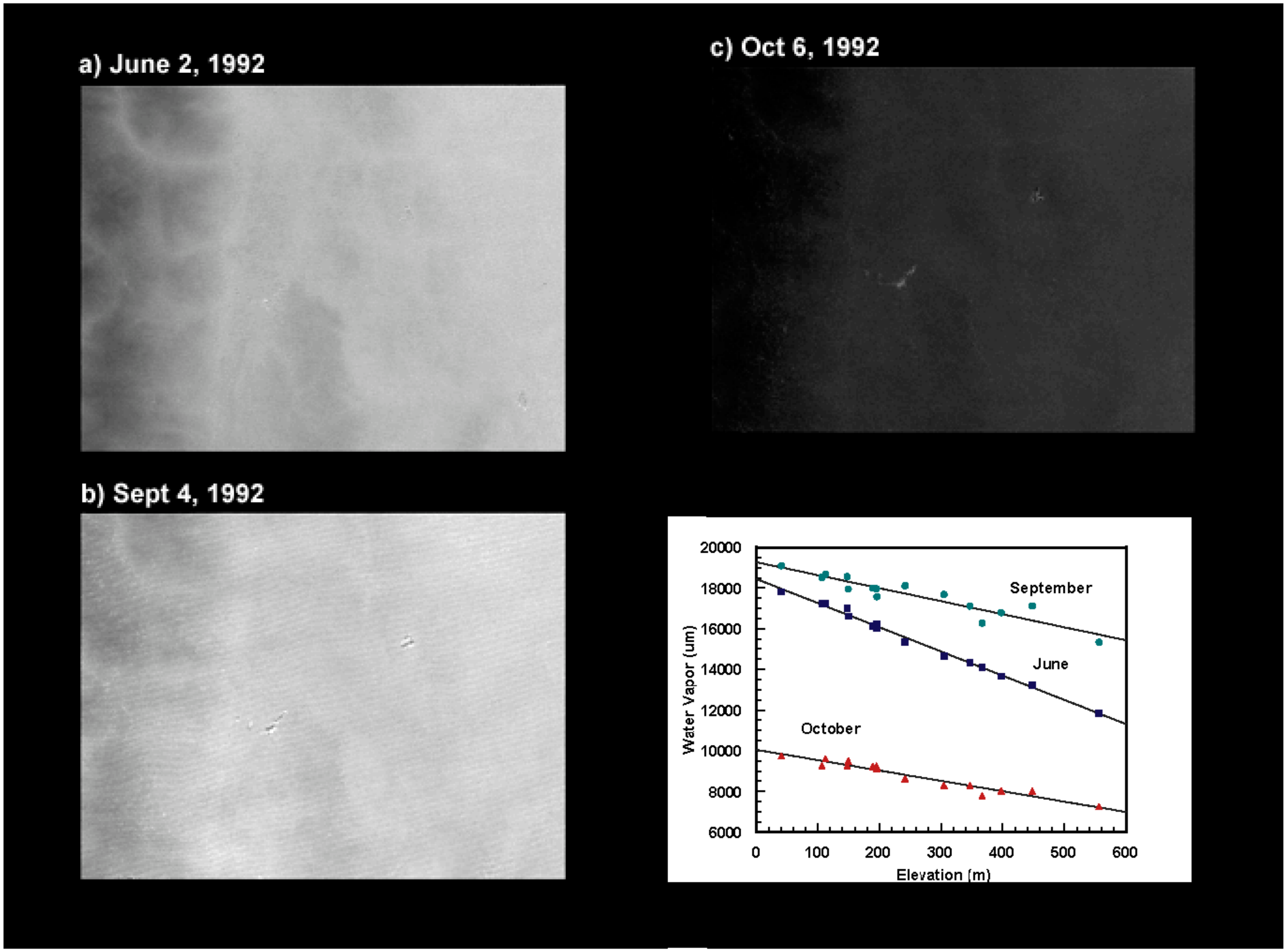
Reflectance Product: Water vapor and Liquid water



- Liquid water
  - Measures water in leaves
  - Primarily structural
- Water vapor
  - Inversely related to topography
  - Varies temporally
  - Related to ET

Roberts et al., 1997, RSE

Temporal Changes in Water Vapor



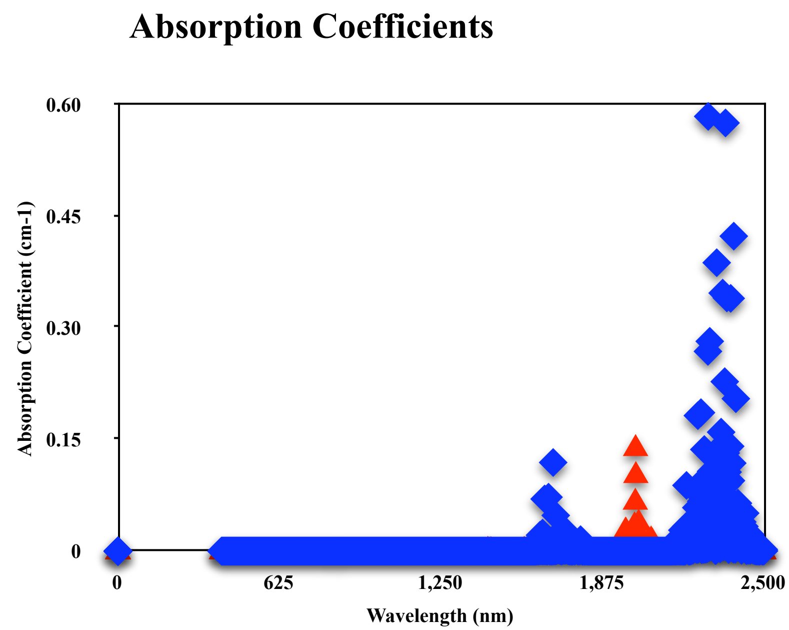
Roberts et al., 1997, RSE

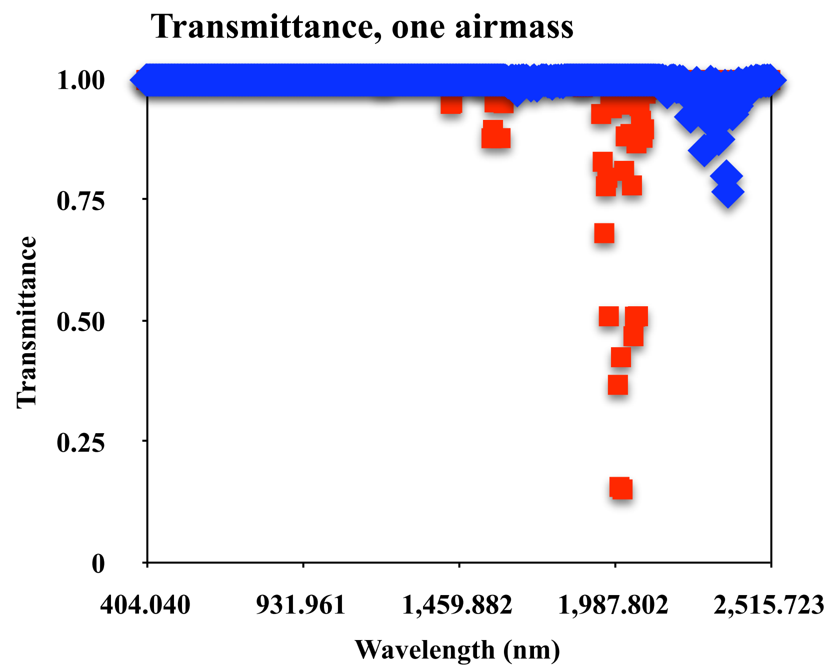
Can Methane be Mapped With Hyper-Spectral Sensors?

Courtesy of Dar Roberts
UCSB

Why Map Methane?

- Methane is a strong greenhouse gas with large absorption coefficients at ~2300 nm and 1700 nm
- Methane is a far stronger absorber than Carbon Dioxide but has a lower impact because of a much lower concentration in the atmosphere
  - CO_2: ~ 370 ppm
  - CH_4: ~ 1.9 ppm





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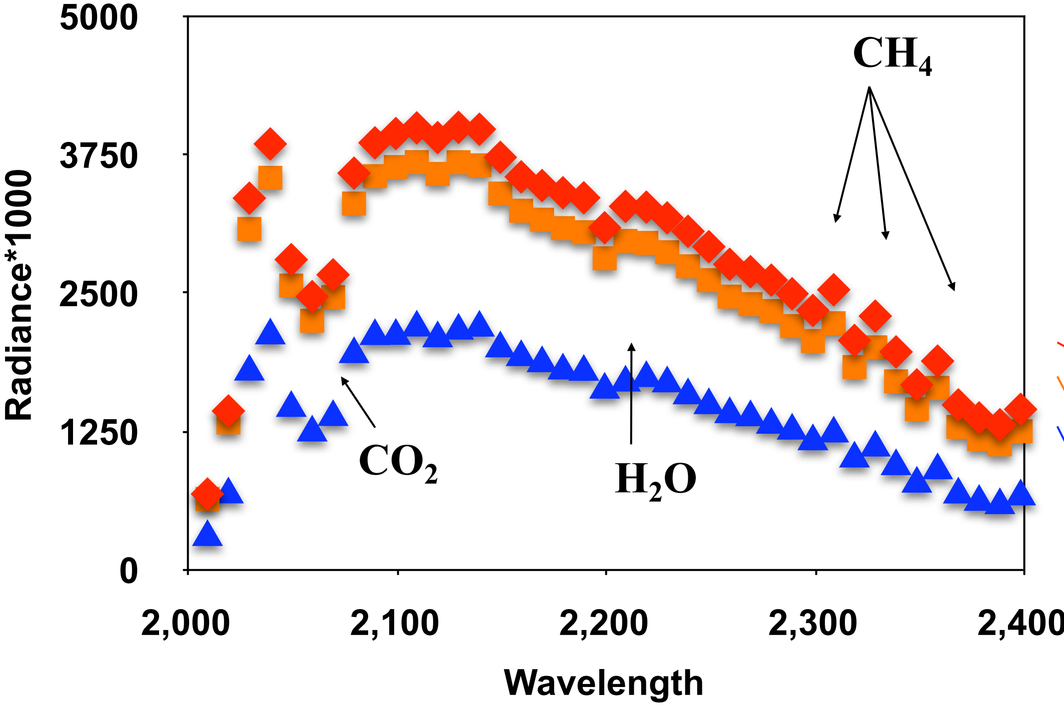
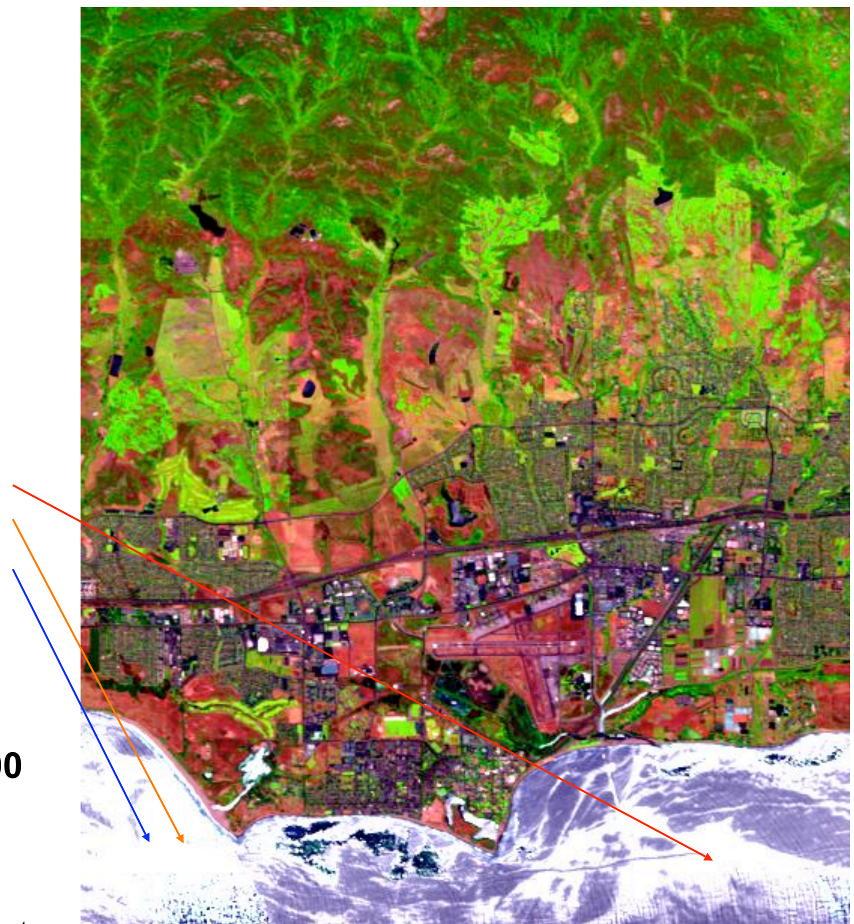
AVIRIS Measures of Methane
6-14-2001





Note differences in surface reflectance
Note atmospheric background methane is prominent

Courtesy of Dar Roberts
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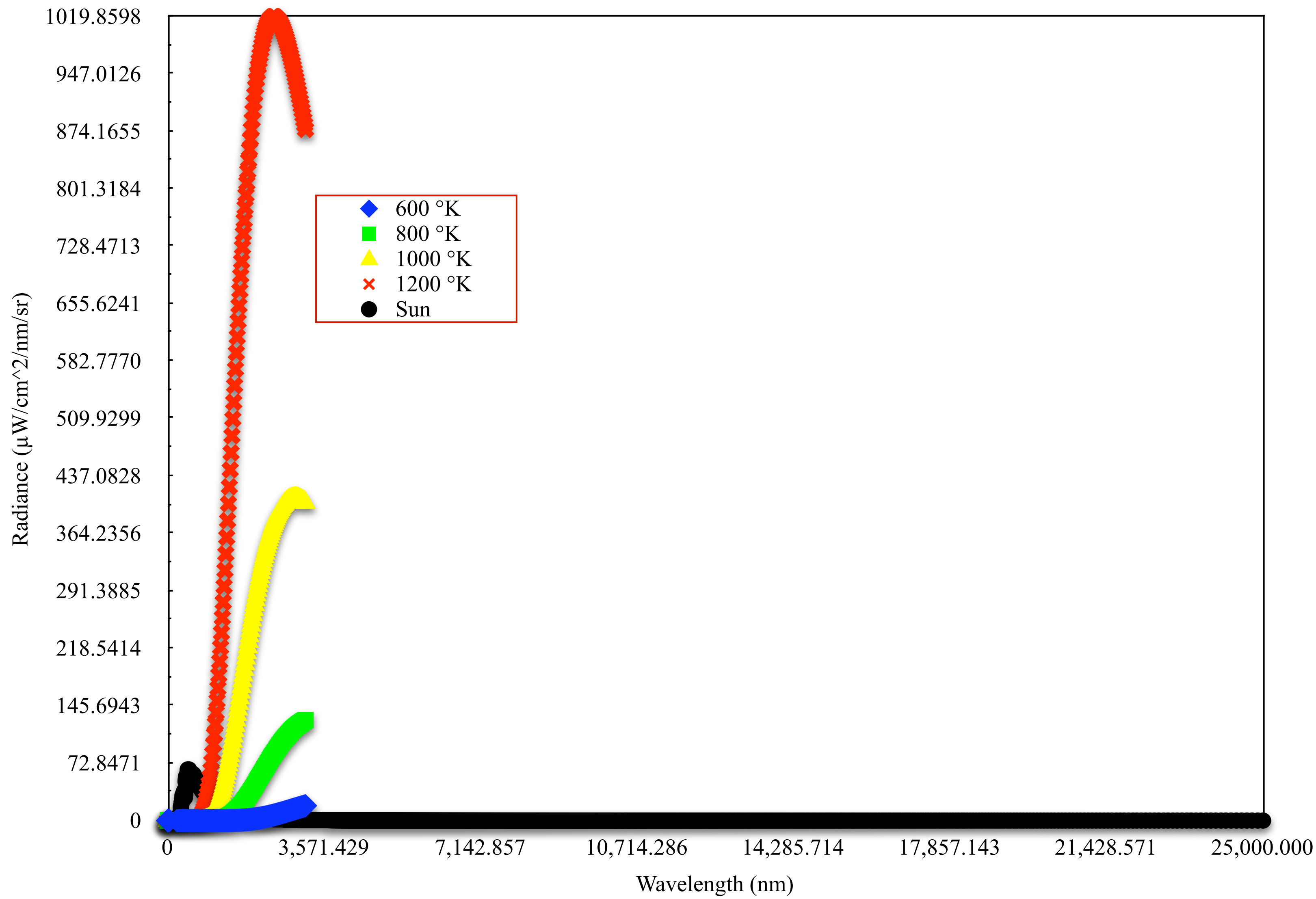
Fire Temperature Retrievals

- The primary focus on fire temperature retrieval has been in the thermal
- Thermal systems tend to saturate at high fire temperatures
- In imaging spectrometer, similar to AVIRIS provides a wide range of temperature retrievals
  - 500K to over 1500K
  - The system cannot saturate because there is always a signal at shorter wavelengths

Courtesy of Dar Roberts
UCSB

Planck Functions and The Solar Irradiance Spectrum



From Robert Green

Methods

- **Multiple Endmember Spectral Mixture Analysis (MESMA) was used to model each pixel in the AVIRIS image**
- **Each pixel was modeled as a combination of:**
  - **1 emitted thermal radiance endmember**
  - **1 reflected solar radiance endmember**
  - **Shade (zero radiance)**
- **Emitted thermal radiance endmembers were modeled using MODTRAN**
  - **Ranged from 400-1500 K (260°-2240°F) at increments of 10 K**
- **Reflected solar radiance endmembers were selected from the image using Endmember Average RMSE (EAR)**
  - **Six possible endmembers: riparian, dense chaparral, sparse chaparral/ sagescrub, grass, soil and ash**

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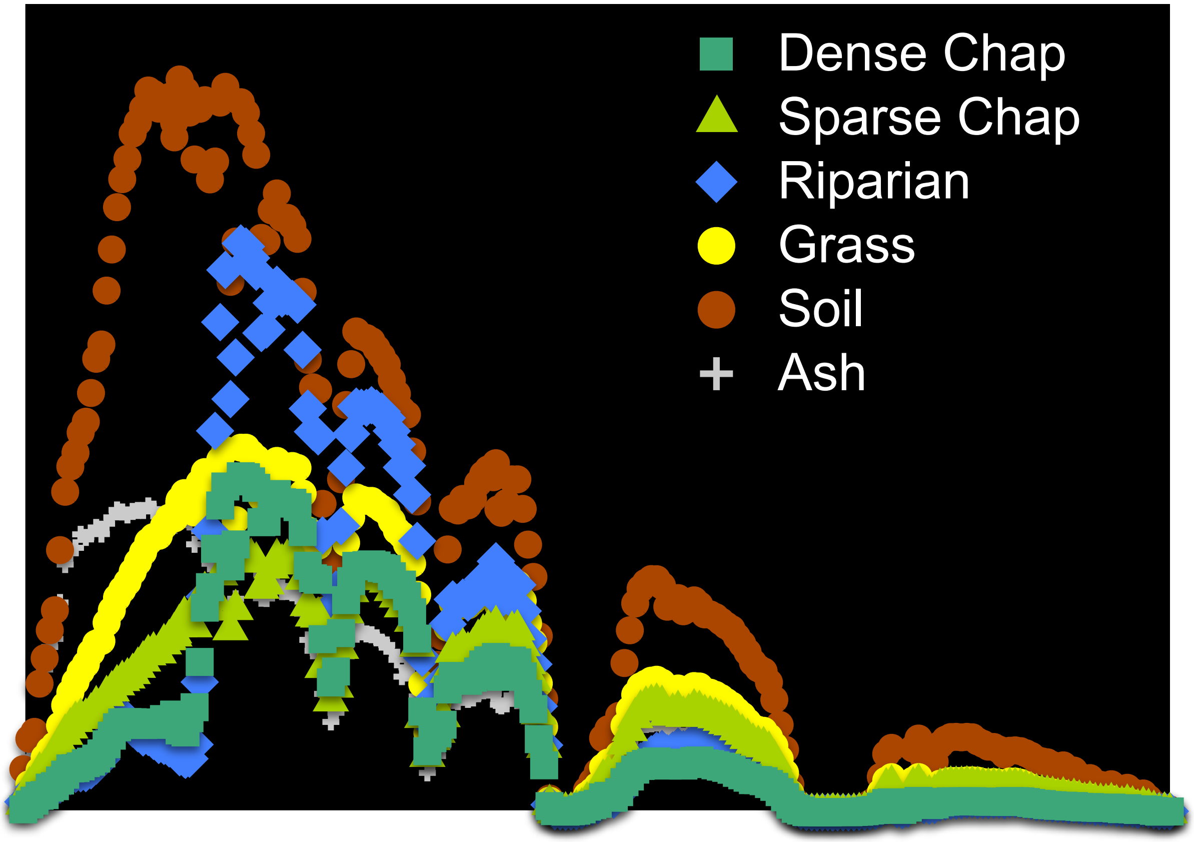
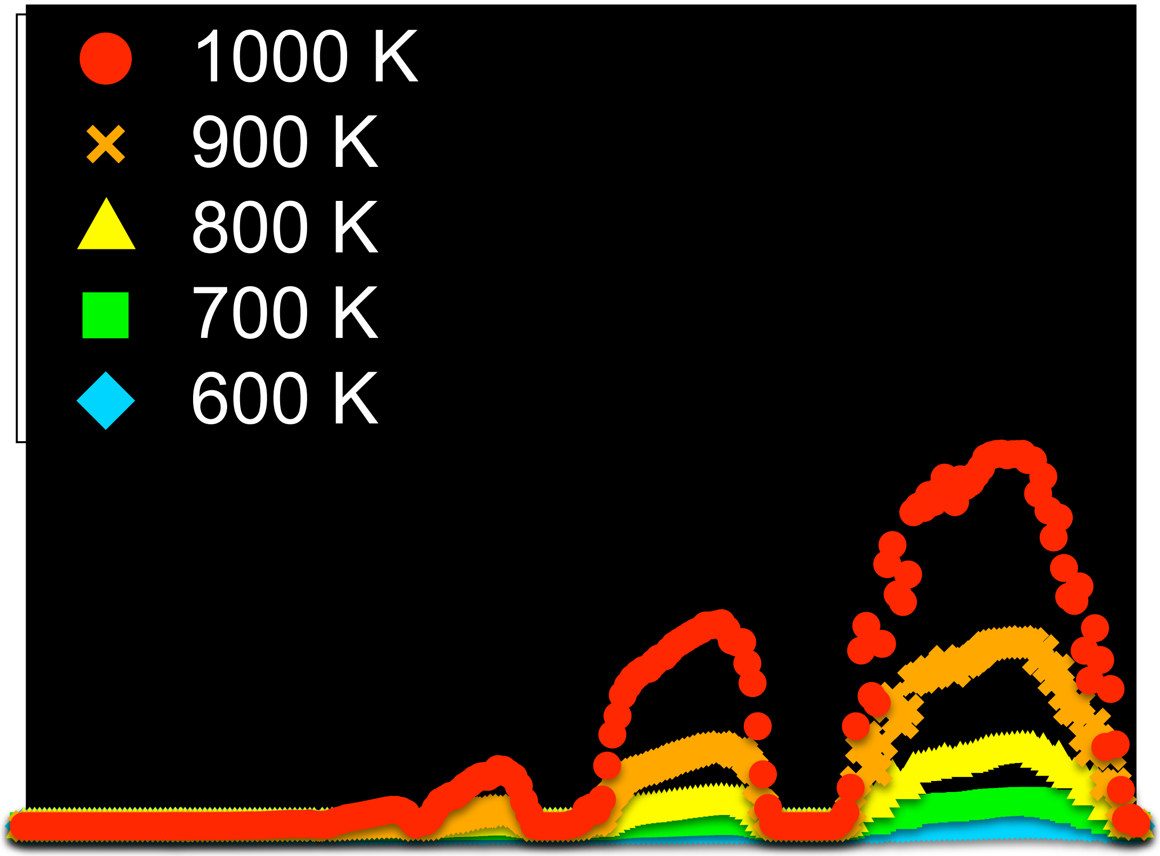
Reflected Solar Radiance Endmembers



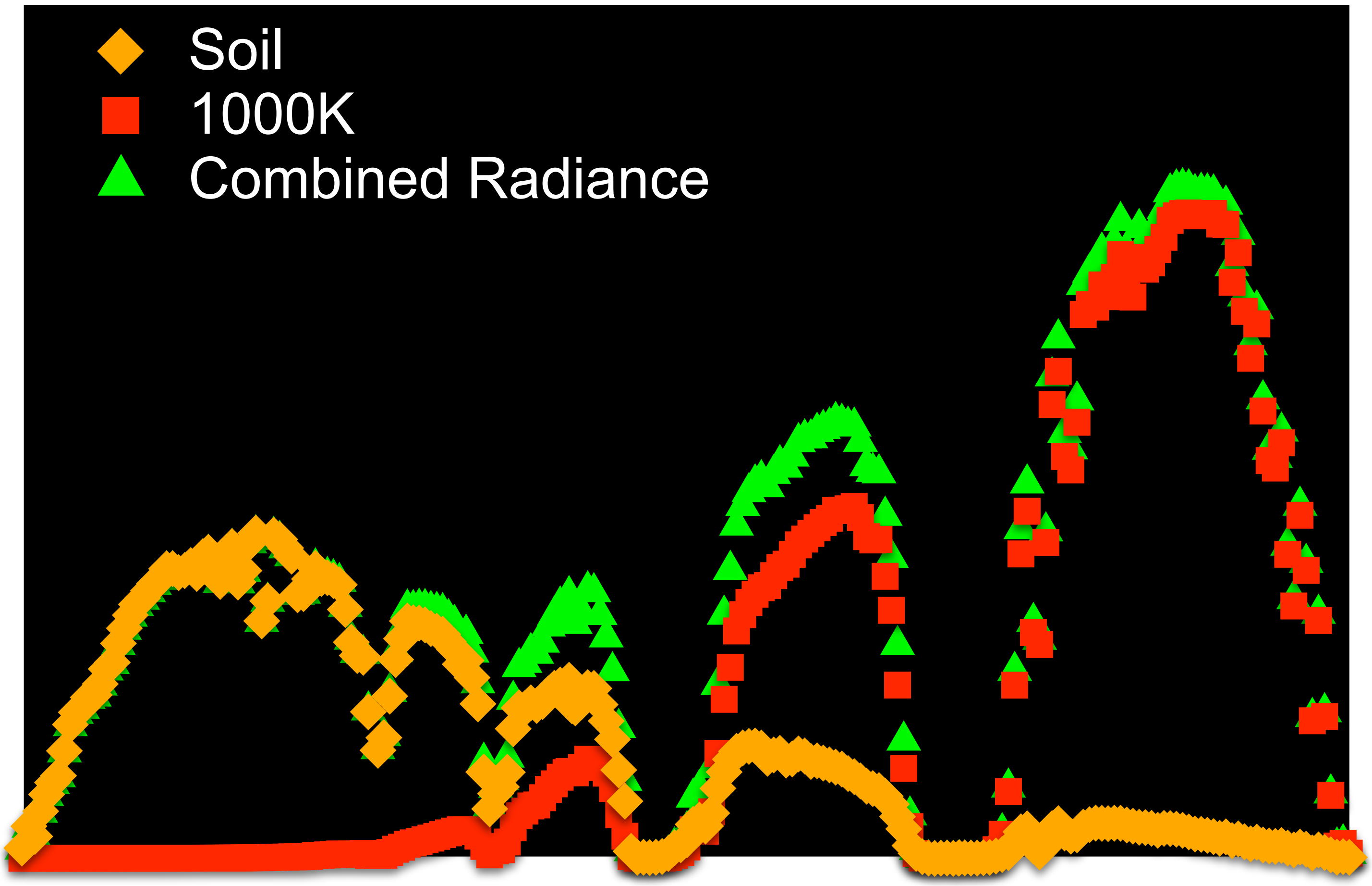
Dennison et al., 2005

Subset of Emitted Thermal Radiance Endmembers



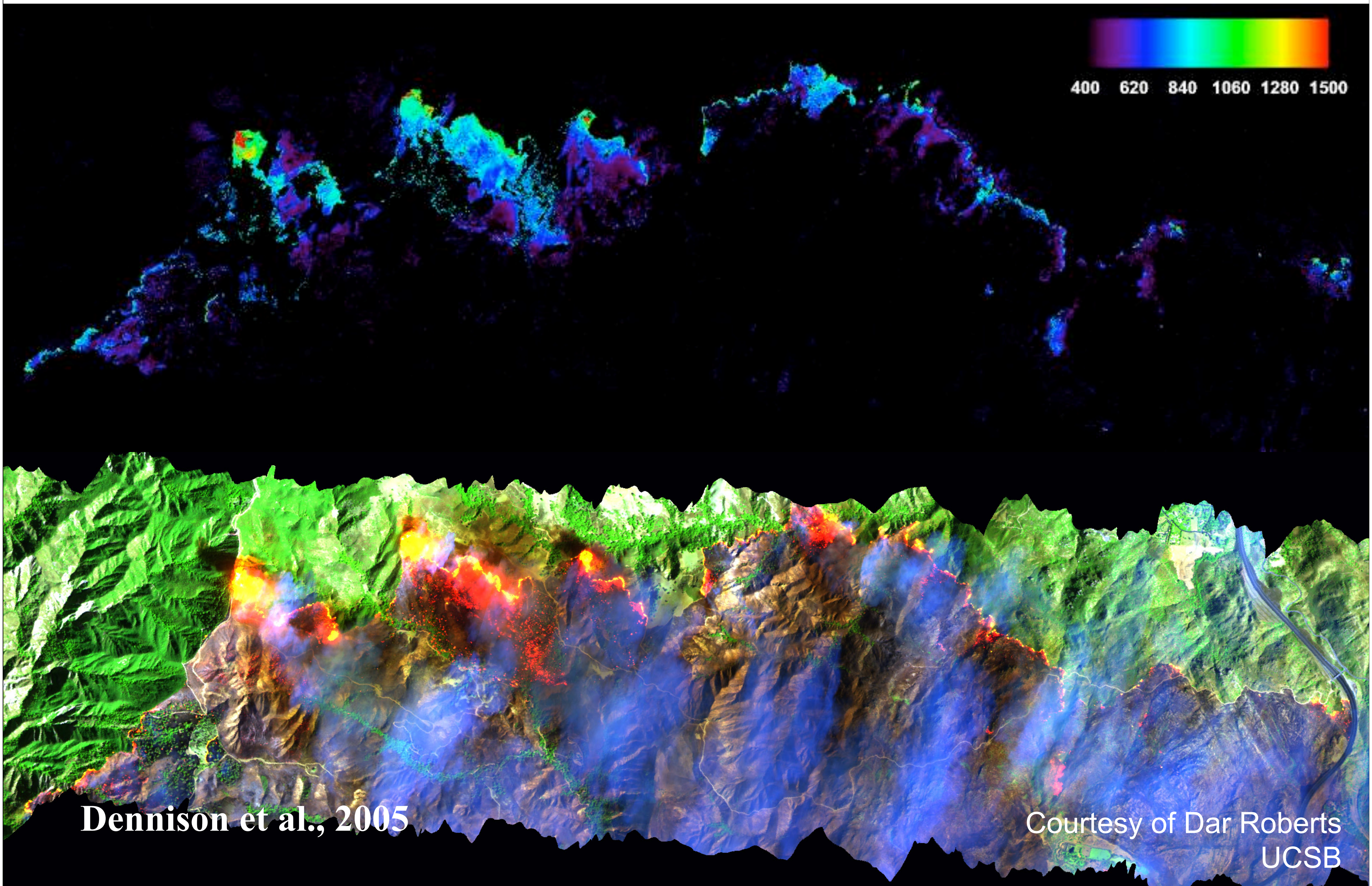
Dennison et al., 2005

Example: Mixed Radiance

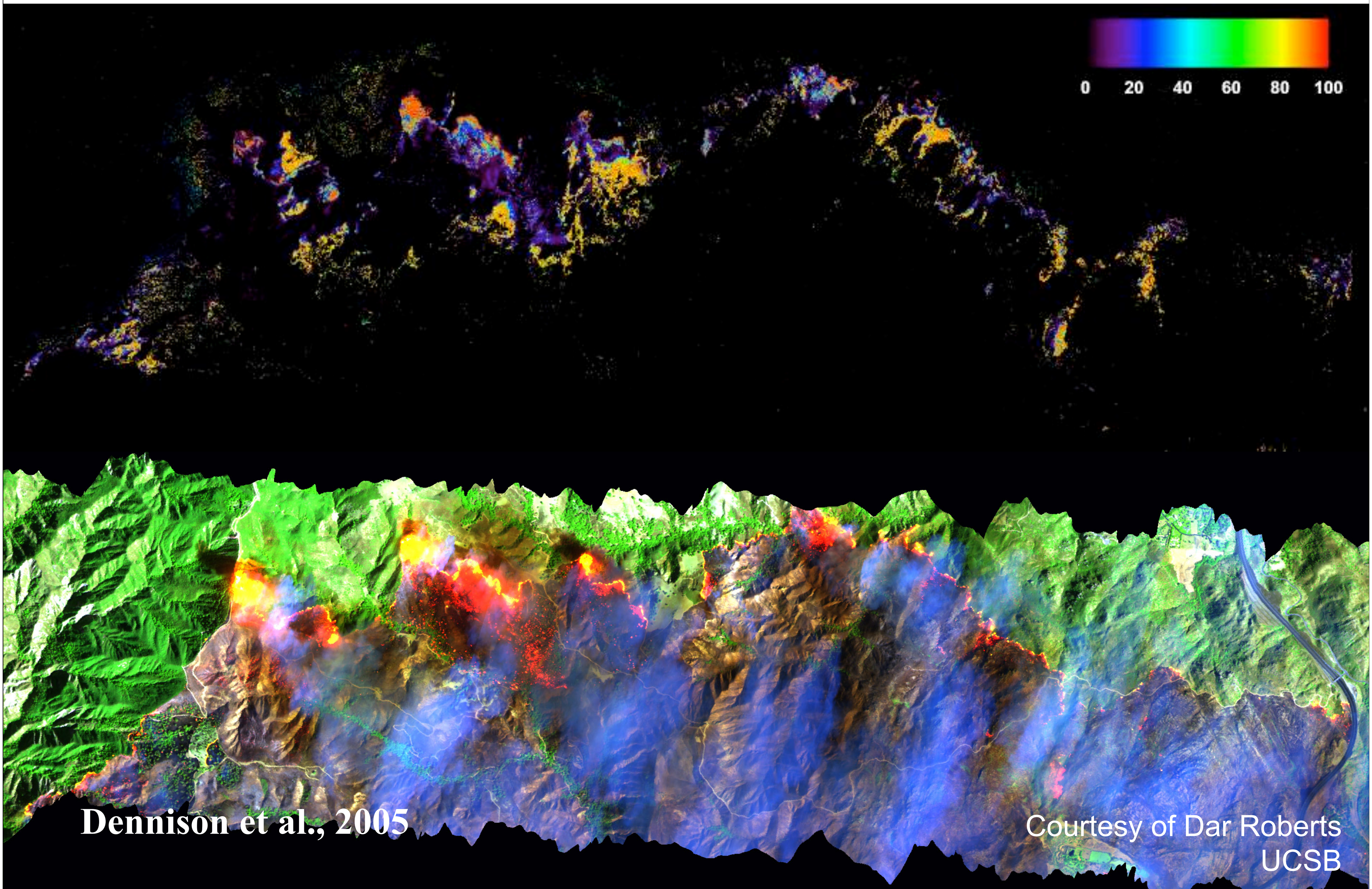


Dennison et al., 2005

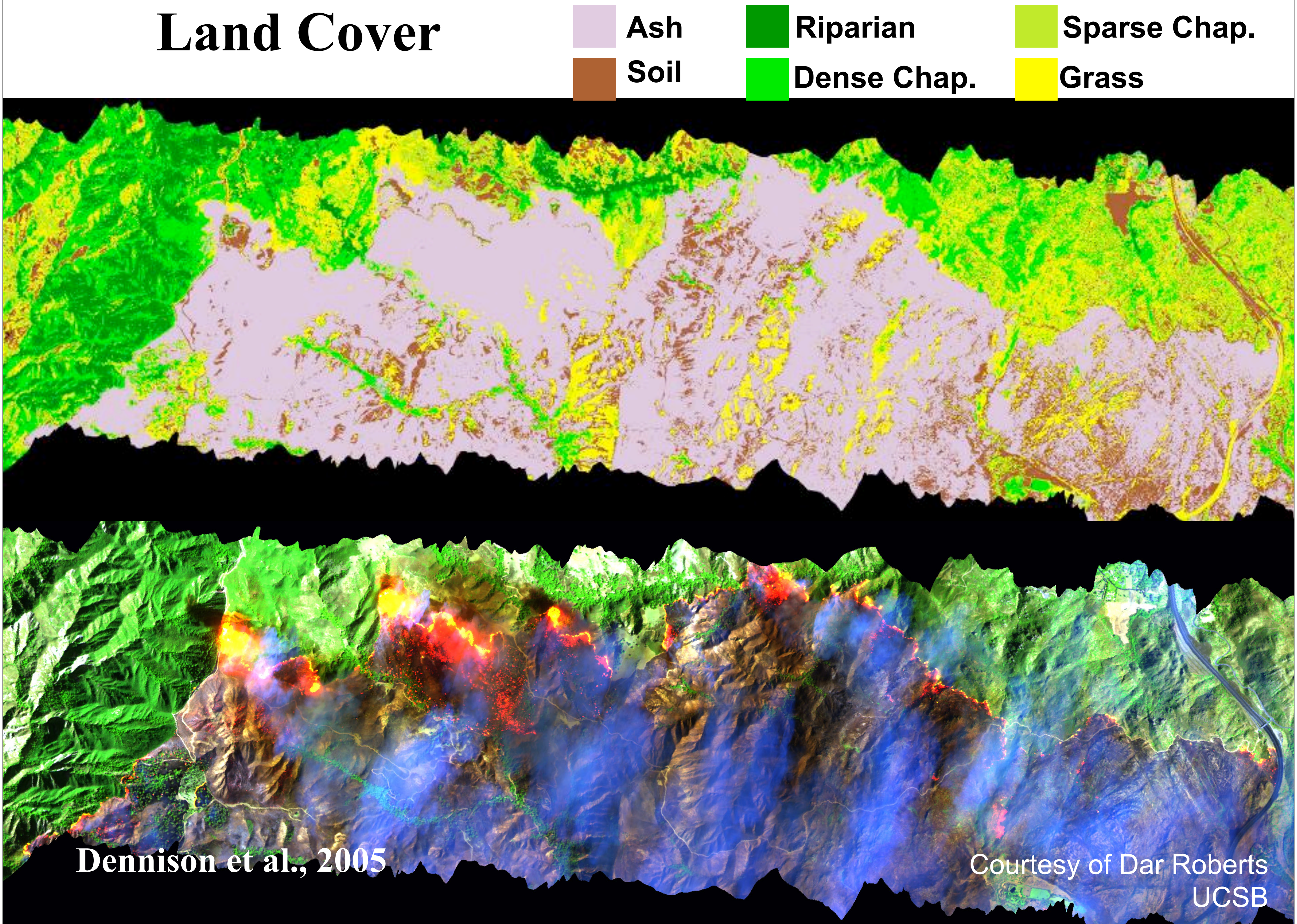
Retrieved Temperature Endmembers



Retrieved Temperature Fraction



Land Cover


Ash
Soil
Riparian
Dense Chap.
Sparse Chap.
Grass
Dennison et al., 2005
Courtesy of Dar Roberts
UCSB

Motivation for Urban Environments

- Urban Environments are Challenging
  - The diversity of materials is high
  - The scale at which surfaces are homogeneous is typically below the spatial resolution of spaceborne and airborne sensors
- New Remote Sensing Technologies need to be Evaluated
  - Hyperspectral: AVIRIS, Hyperion, HYMAP
  - Hyperspatial: IKONOS Panchromatic
  - LIDAR: Fine vertical resolution
  - SAR: Interferometry

Courtesy of Dar Roberts
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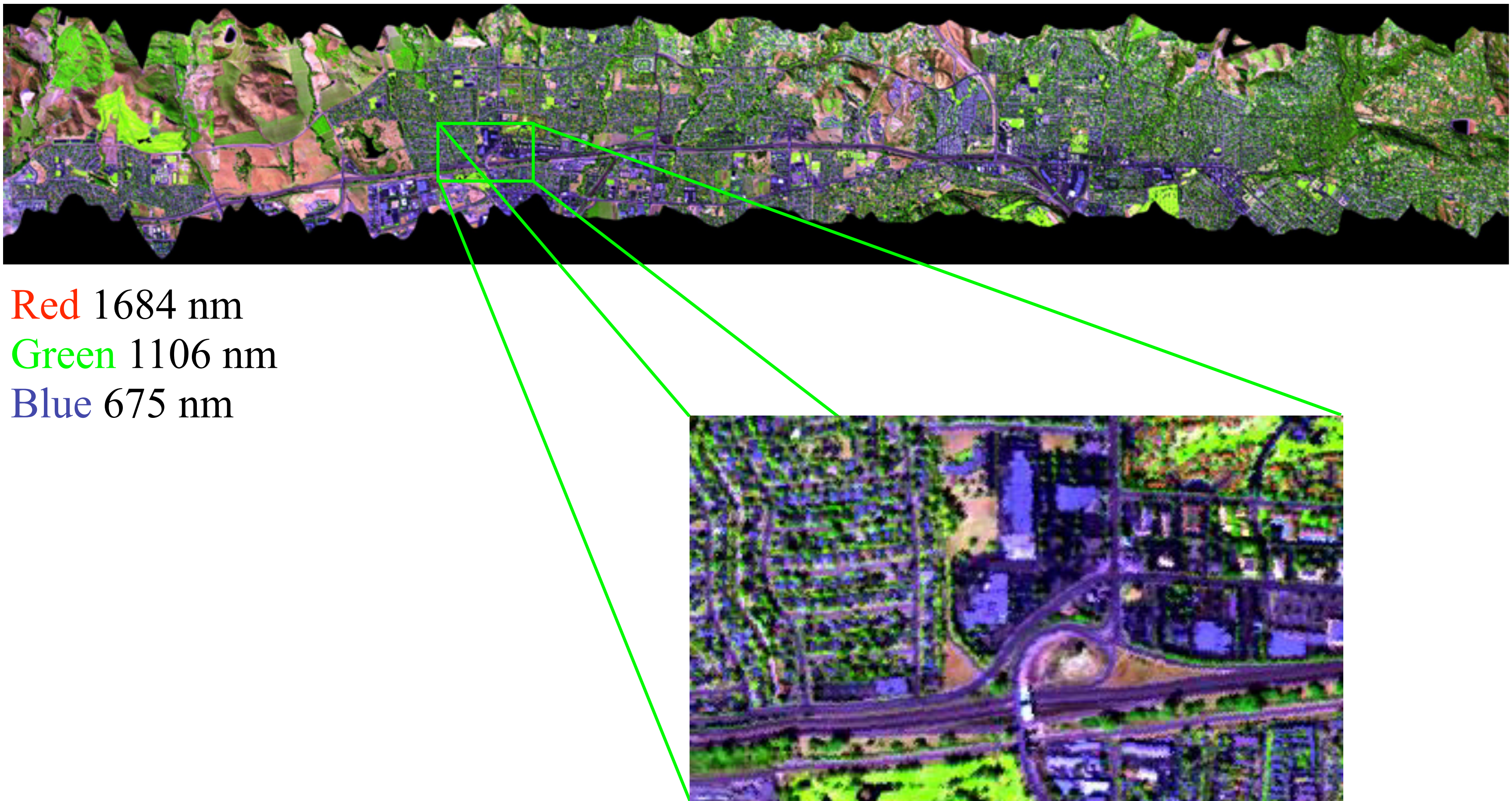
AVIRIS - Santa Barbara, California

Oct 11, 1999 low-altitude data - 4 meter GIFOV

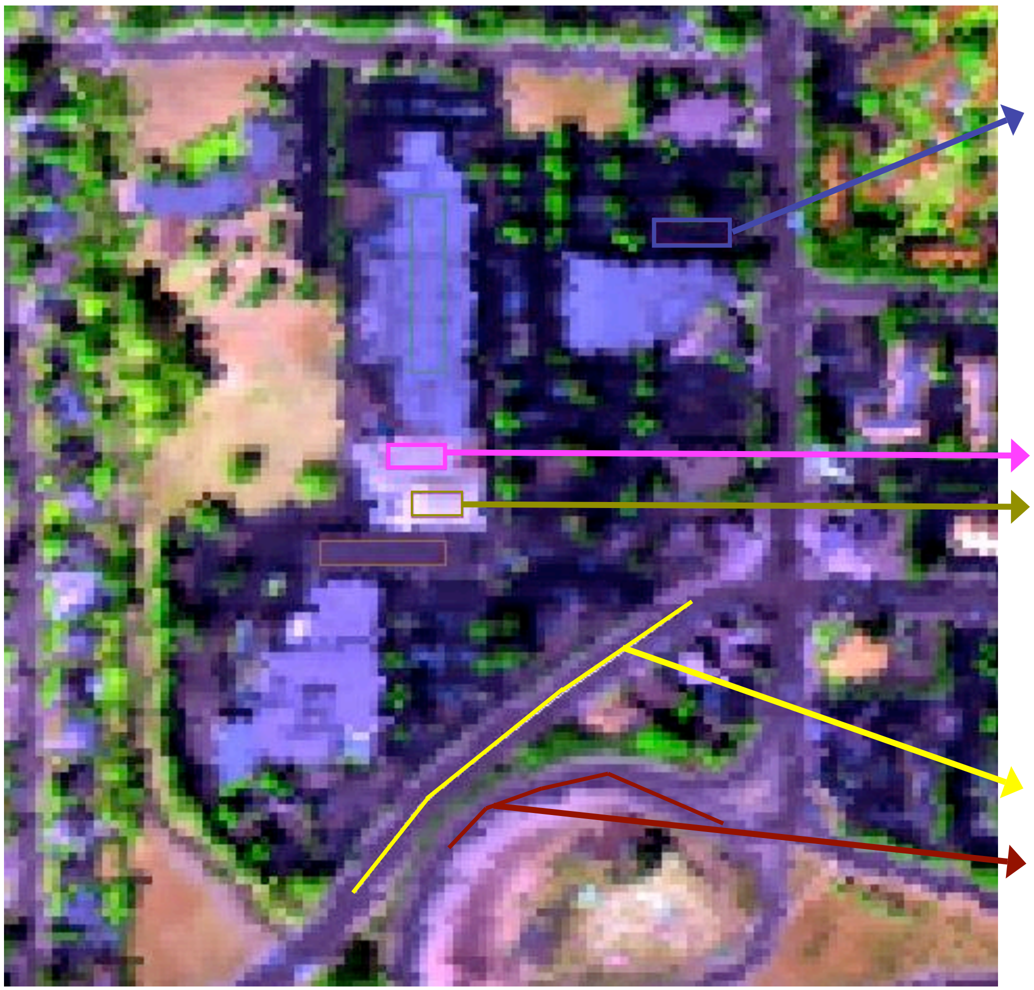


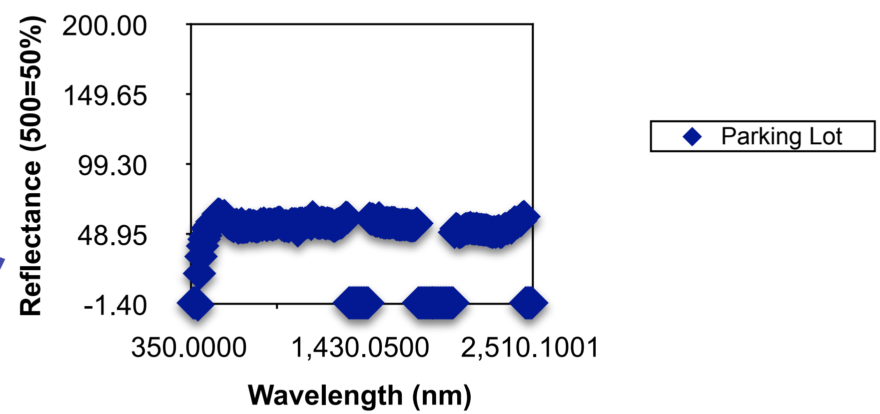
Red 1684 nm
Green 1106 nm
Blue 675 nm

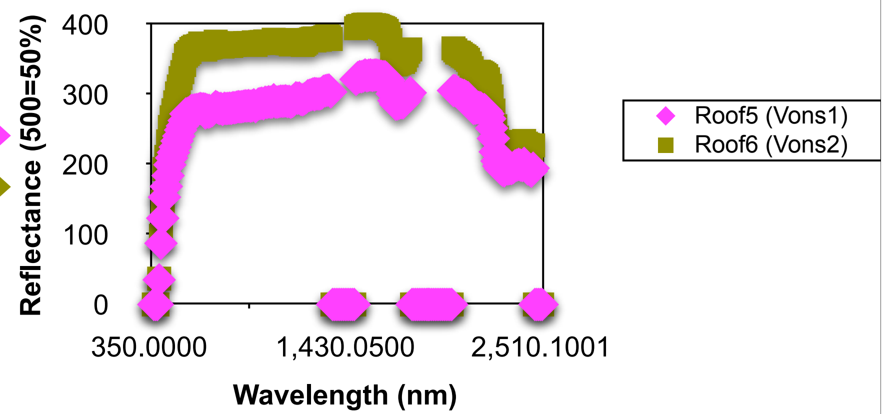
Courtesy of Dar Roberts
UCSB

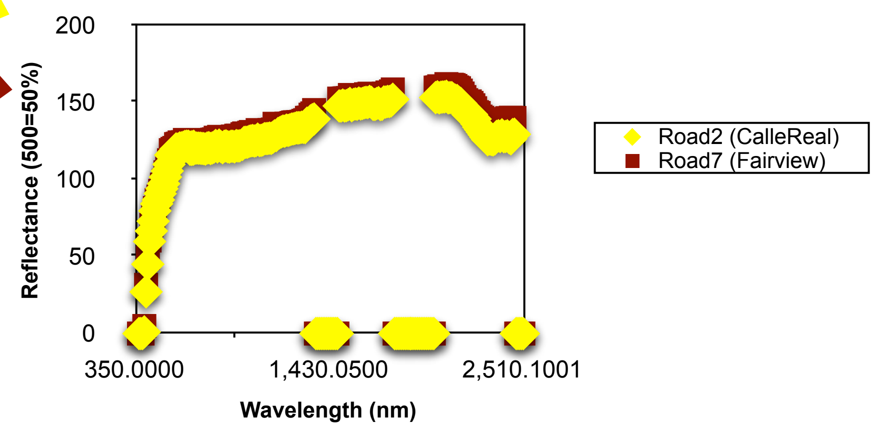
Each pixel is a spectrum

Potential for library development is large









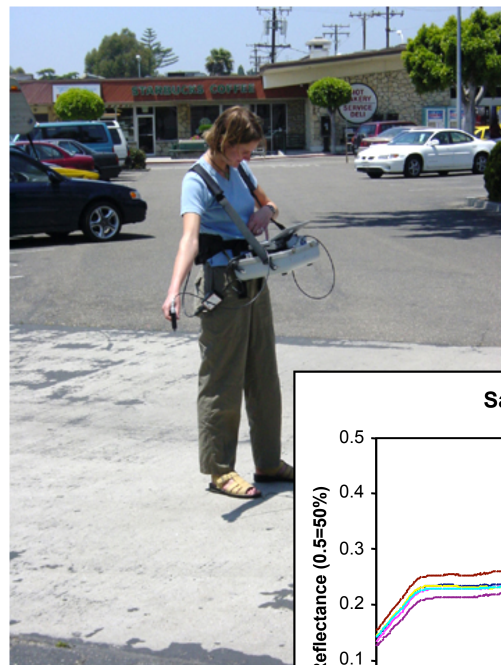
AVIRIS 991011

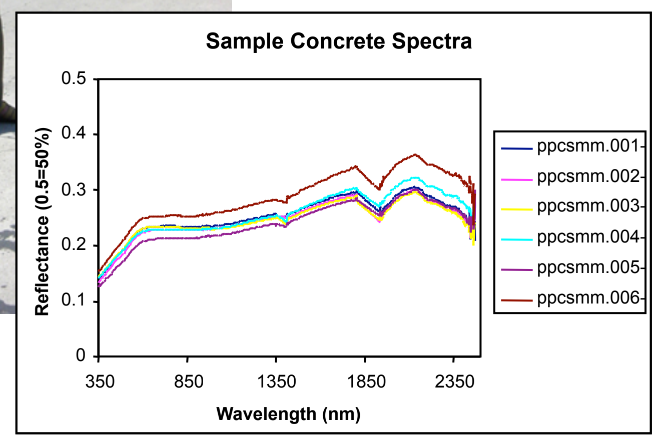
Red = 1684 nm
Green = 1106 nm
Blue = 675 nm

Courtesy of Dar Roberts
UCSB

Field Spectra Summary

- **Over 6,500 urban field spectra were collected throughout Santa Barbara in May & June 2001**
- **Field spectra were averaged in sets of 5 and labeled appropriately in building the urban spectral library**
- **The resulting urban spectral library includes:**
  - **499 roof spectra**
  - **179 road spectra**
  - **66 sidewalk spectra**
  - **56 parking lot spectra**
  - **40 road paint spectra**
  - **37 vegetation spectra**
  - **47 non-photosynthetic vegetation spectra**
    - **(ie. Landscaping bark, dead wood)**
  - **27 tennis court spectra**
  - **88 bare soil and beach spectra**
  - **50 miscellaneous other urban spectra**





Courtesy of Dar Roberts
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Example Spectra: Roofs

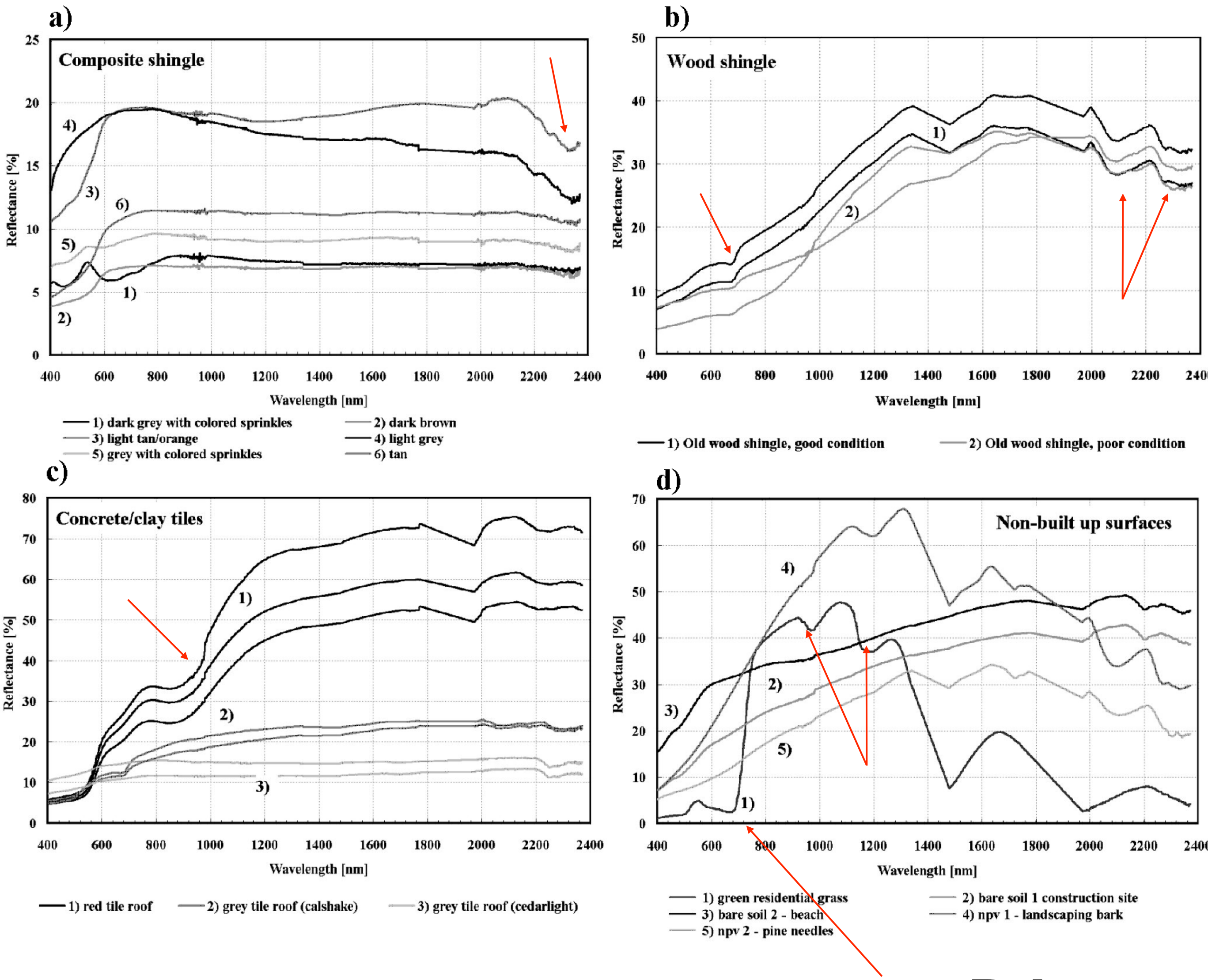


Figure 5

Key Absorptions

Composite Shingle: carbonates, asphalt

Wood Shingle: ligno-cellulose

Tile: iron-oxides

Plants: Liquid water, chlorophyll, ligno-cellulose

Note, age is important

Roberts and Herold, 2004

Example Spectra: Transportation Surfaces

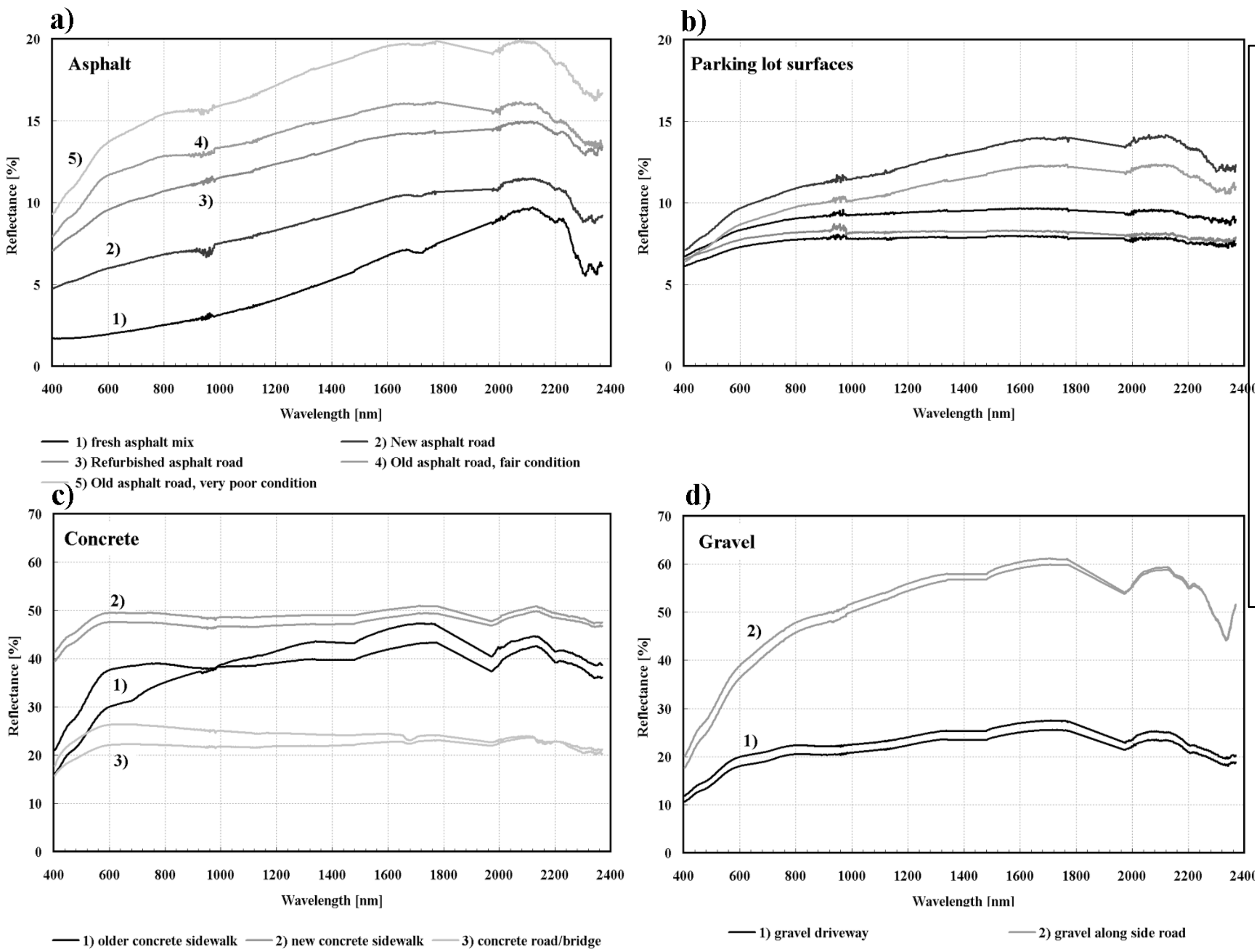


Figure 6

Key Absorptions

Asphalt: Hydrocarbons, aging

Parking lots: featureless, dark

Concrete: carbonates?

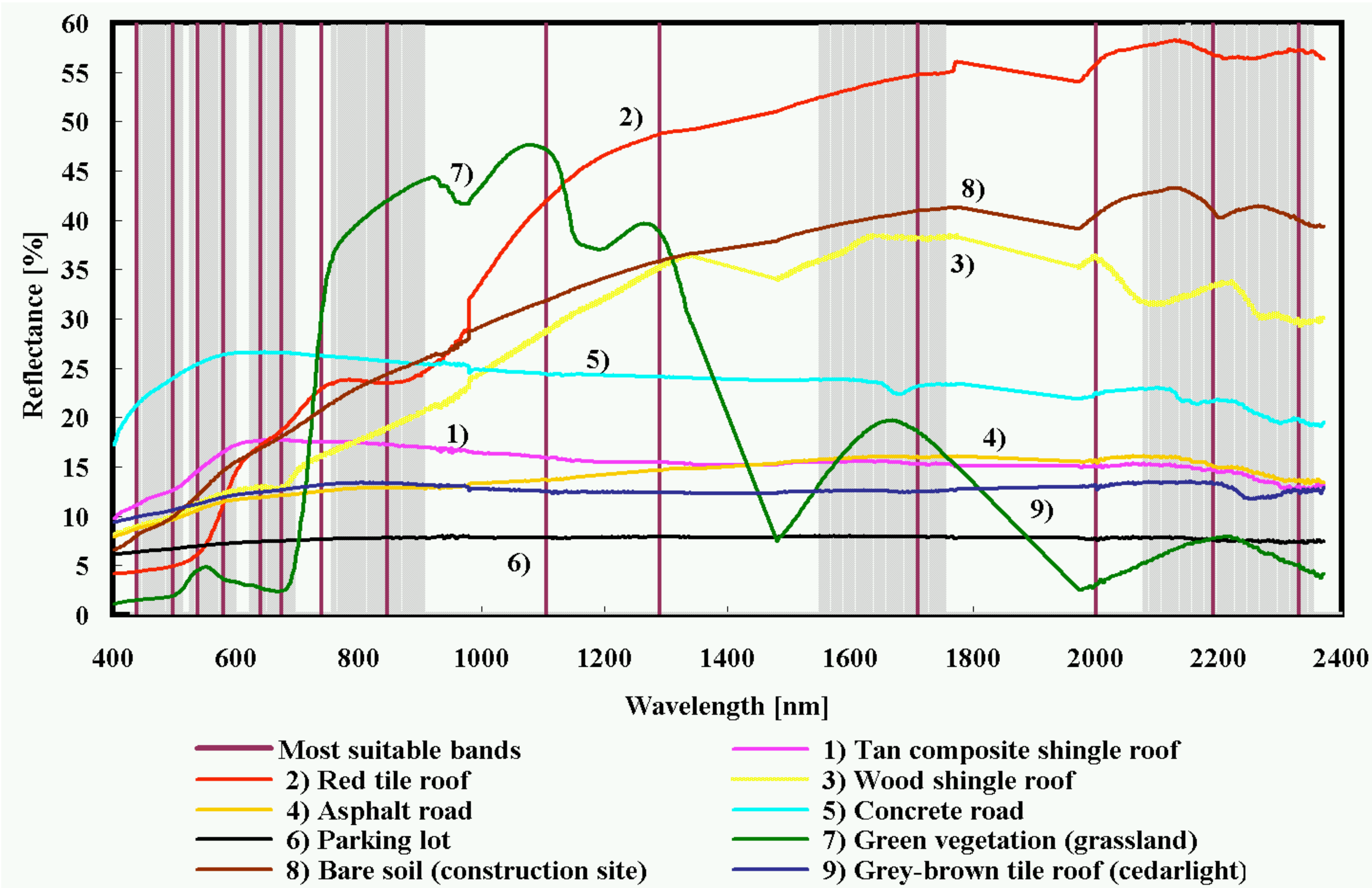
Gravel: depends on source material

Concretes darken with age

Pavement gets brighter

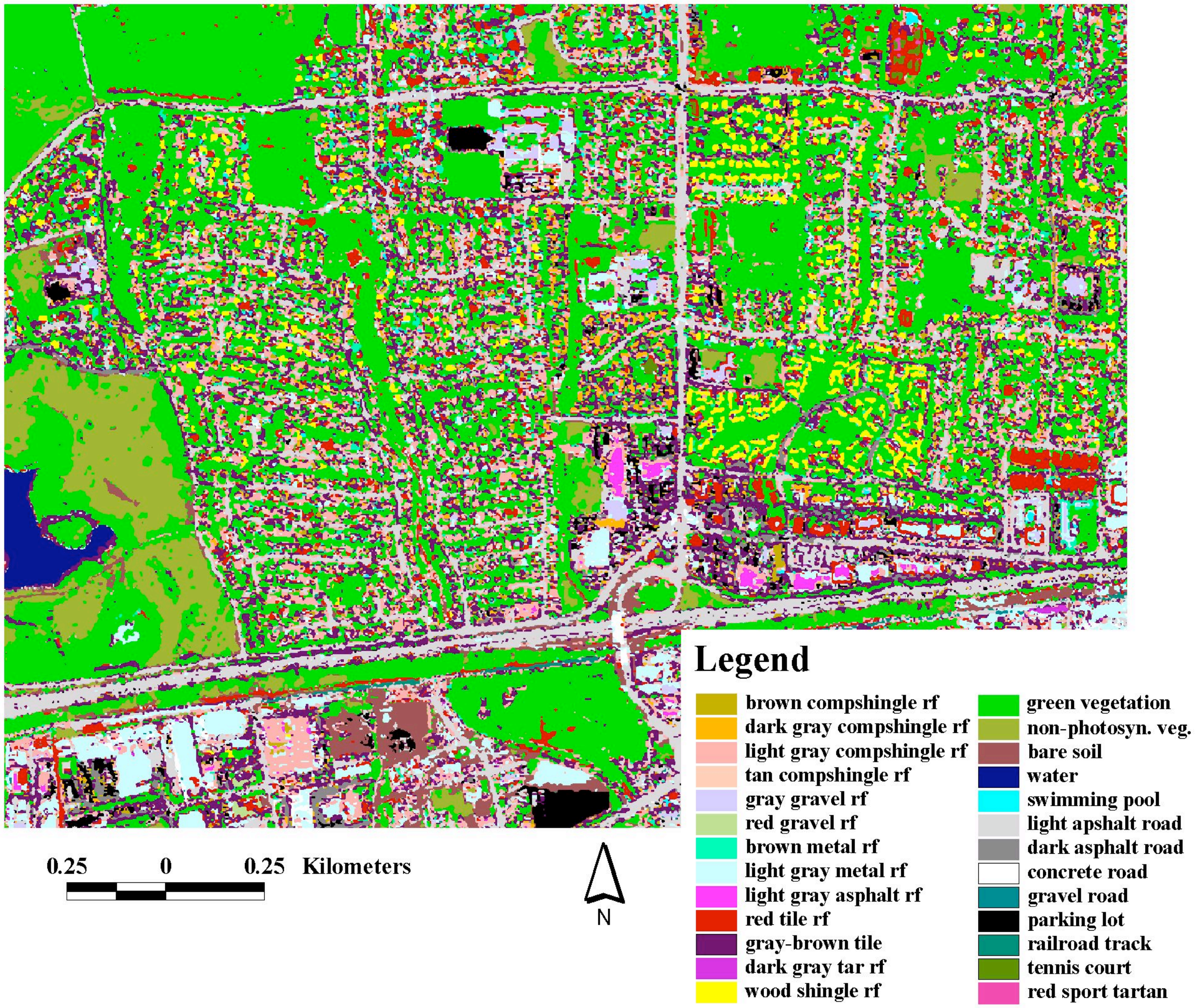
Roberts and Herold, 2004

Most suitable spectral bands
Top 14 selected based on Bhattacharyya -distance



From: Herold M., Gardner M. and Roberts D. 2003. Spectral Resolution Requirements for Mapping Urban Areas, IEEE Transactions on Geoscience and Remote Sensing, 41, 9, pp. 1907-1919

Land cover mapping



- 14 most suitable bands
- 26 land cover classes
- 22 built up classes
- Inter-class confusion confirms sep. analysis
- Spectral limitations:
  - # and location of bands
  - Narrow vs. broadband

Overall Accuracy

	Mean accuracy	Kappa coefficient	Area weighted accuracy	Built classes accuracy
IKONOS (4 bands)	61.8 %	60.2 %	66.6 %	37.7 %
Landsat TM (6 bands)	68.9 %	67.7 %	75.8 %	53.9 %
AVIRIS (14 bands)	73.5 %	72.5 %	82.0 %	66.6 %

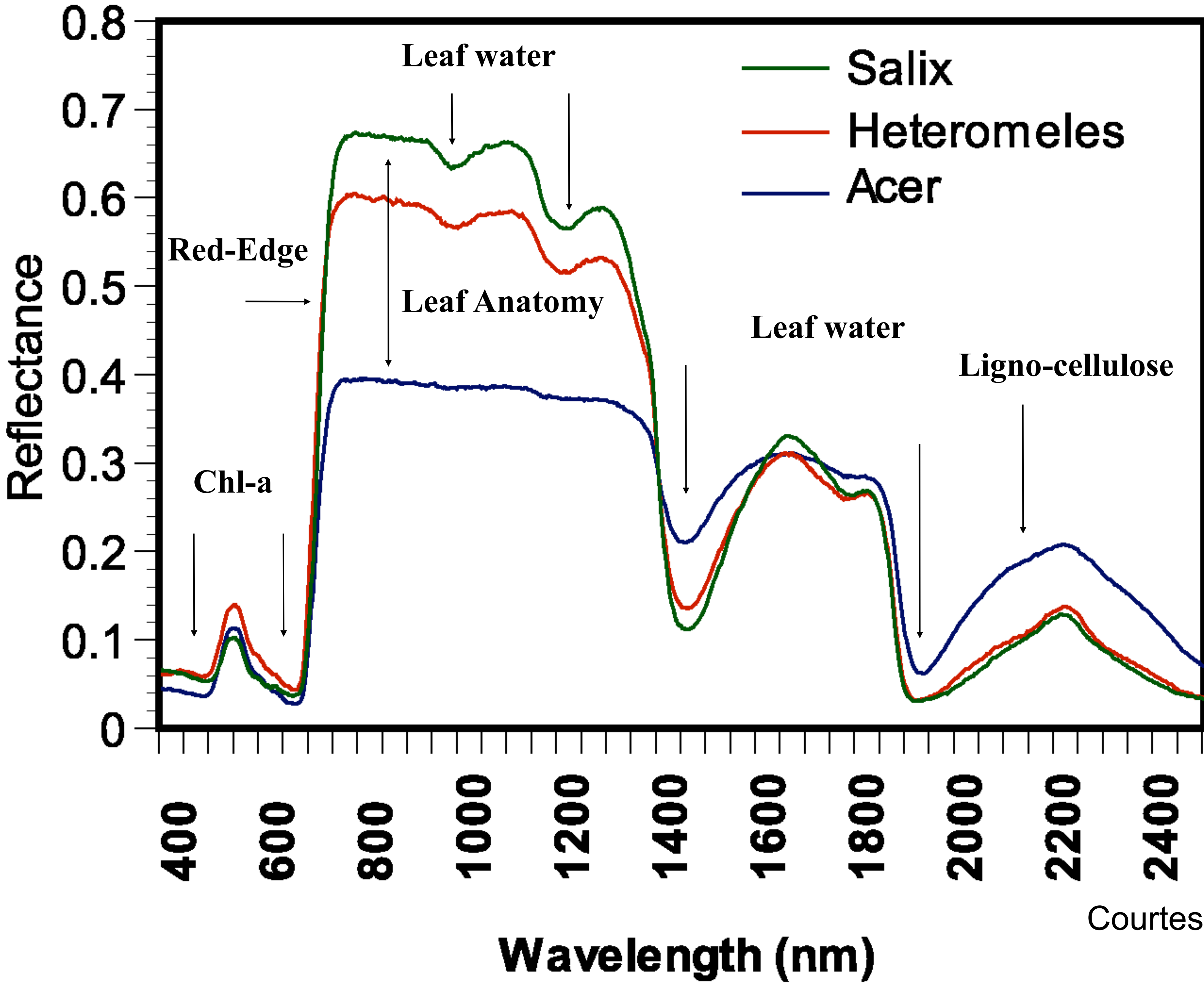
From: Herold M., Gardner M. and Roberts D. 2003. Spectral Resolution Requirements for Mapping Urban Areas, IEEE Transactions on Geoscience and Remote Sensing, 41, 9, pp. 1907-1919

Plant Stress and Physiology

- Plant spectra are a product of multiscale processes
  - Leaf
    - Chemistry (pigments, water, ligno-cellulose)
    - Anatomy (thickness, internal structure)
    - Phenology
  - Branch
    - Density, orientation of leaves (LAI, LAD)
    - Exposed branches, litter and soil
  - Canopy and Stand
    - Crown geometry, leaf/branch density
    - Density, percent cover, species composition
- Imaging spectrometry provides detailed information on leaf/branch scale chemistry, architecture and how they change in response to stress

Courtesy of Dar Roberts
UCSB

Spectroscopy of Leaf Chemistry and Anatomy



Courtesy of Dar Roberts
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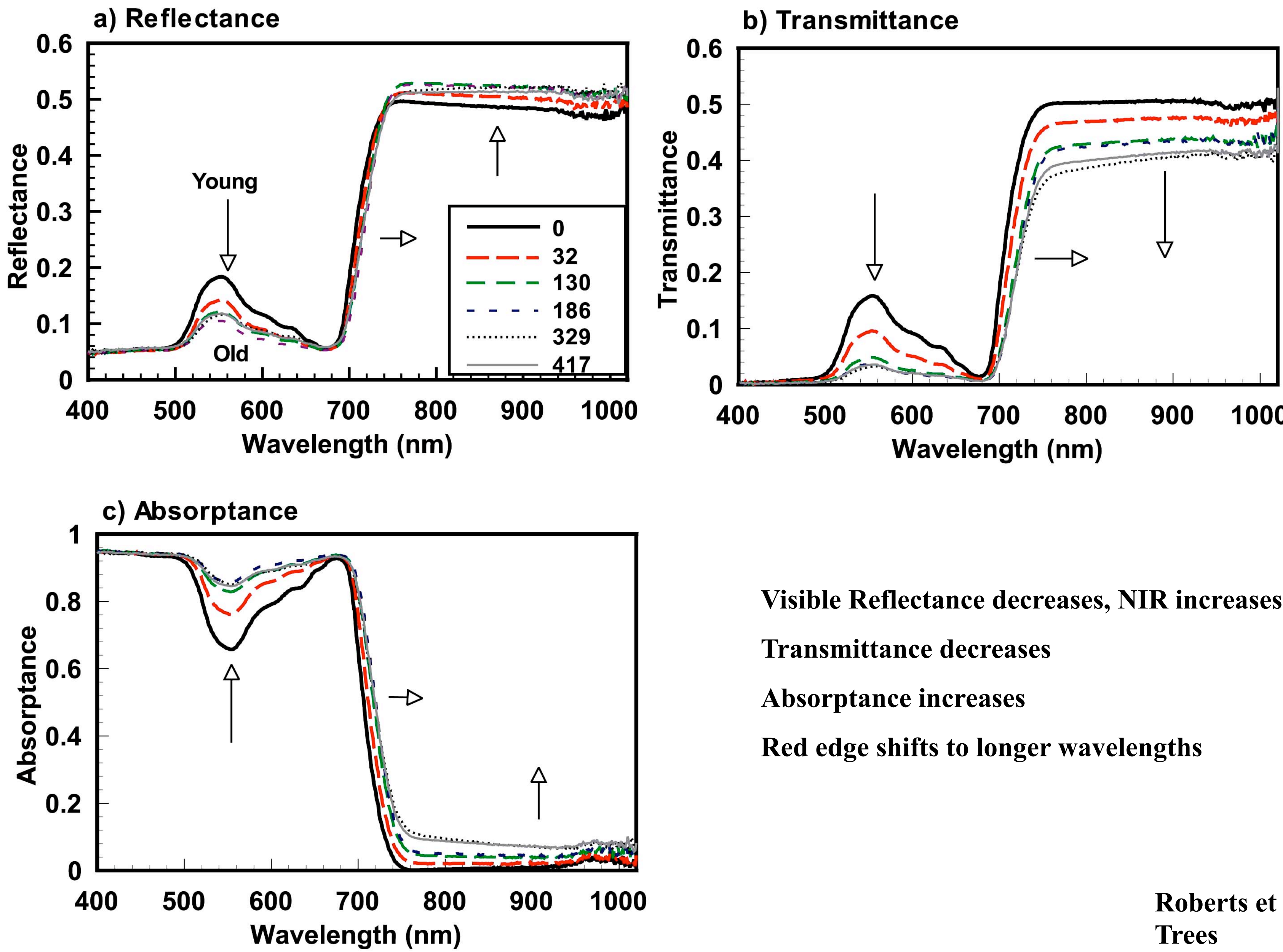
Leaf Aging Effects



Visible Reflectance decreases, NIR increases

Transmittance decreases

Absorptance increases

Red edge shifts to longer wavelengths

Roberts et al. 1998:
Trees

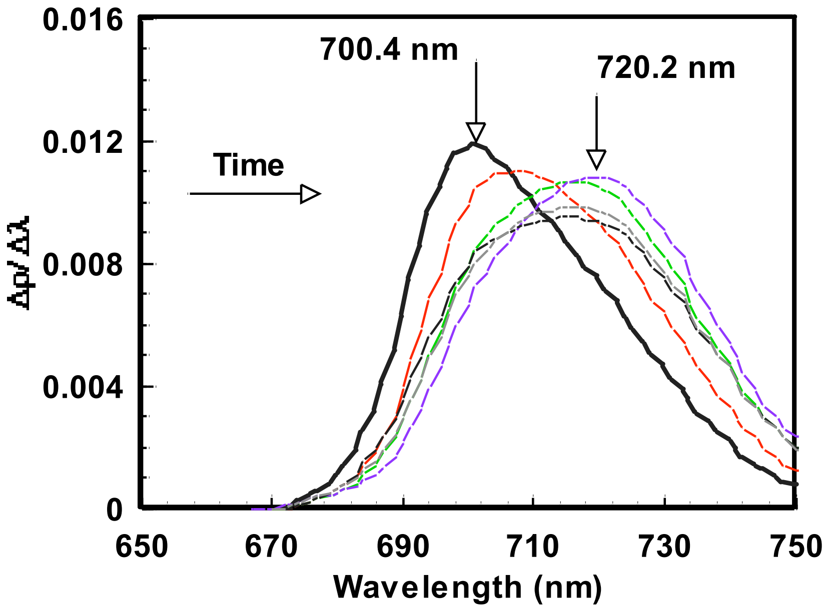
Physiological and Biophysical Measures

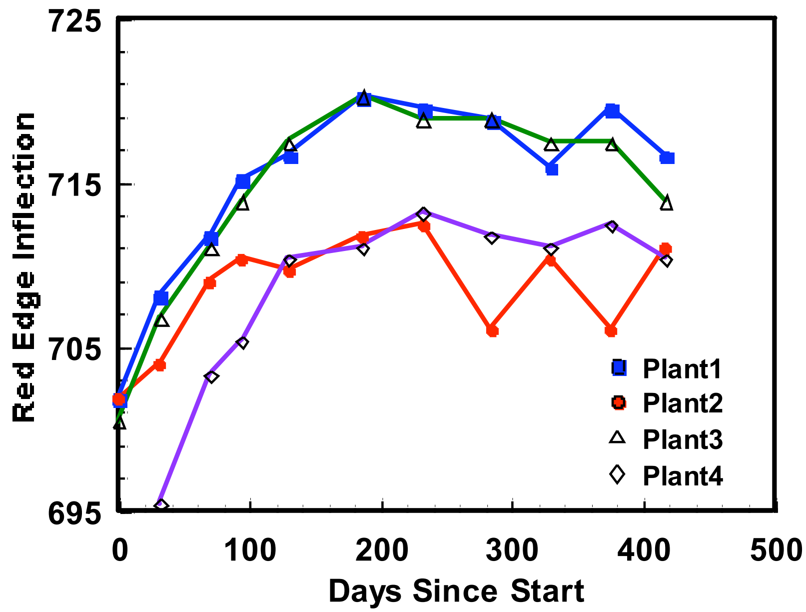
- Pigments
  - Non-linear least squares
  - Red Edge
- Stress
  - Red edge position
- Quantum efficiency
  - PRI
- Moisture
  - WI , NDWI , Water Thickness
- Evapotranspiration
  - Column Water Vapor
- Biophysical Measures
  - LAI, canopy cover, albedo

Courtesy of Dar Roberts
UCSB

Red Edge vs Leaf Age

Aldina heterophylla





Courtesy of Dar Roberts
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Red Edge and Stress

NDVI:

NDVI= $(R_{830}-R_{660})/(R_{830}+R_{660})$

Poor response at 20 m

RVSI **(Merton and Huntington, 1999)**

RVSI = $((R_{714} + R_{752})/2) - R_{733}$

Sensitive, 4 and 20 m

PRI **(Gamon et al., 1992)**

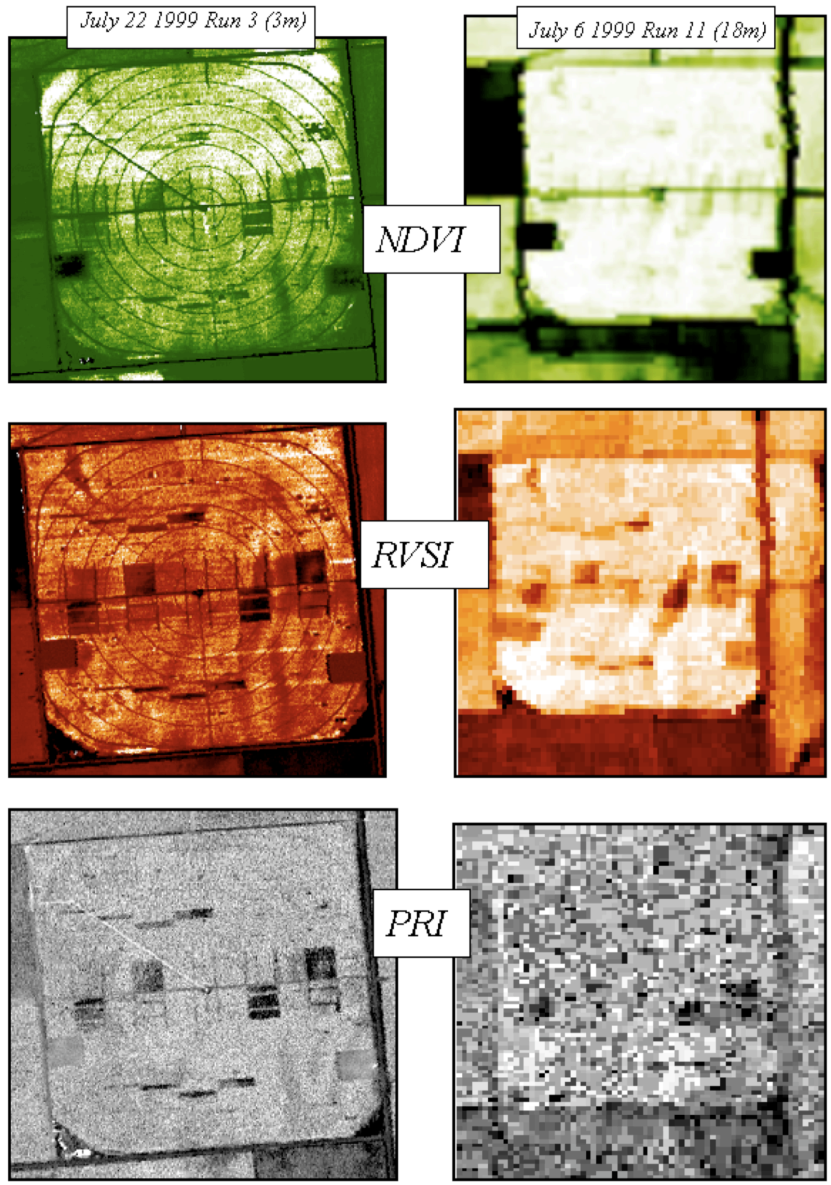
PRI = $(R_{531} - R_{570})/(R_{531} + R_{570})$

Poor response at 20 m

Perry et al., 2002

Shelton NE

NASA EOCAP program



Courtesy of Dar Roberts
UCSB

Summary of Indices: Performance for Nitrogen Stress

Table 7. Ratios of Measured Index Value over Uncertainty[1]

Index	Visibility Uncertainty	1 nm Spectral Shift	2 nm Spectral Shift	View Angles	Reflectance Retrieval
PRI	1.6	0.7	0.4	**6.6**	1.4
NDVI	0.5	14.7	7.2	0.7	1.5
VI	0.4	13.5	6.6	0.7	1.3
SAVI	2.2	**74.1**	**34.9**	1.5	1.6
RVSI	**39.8**	3.9	1.9	**5.7**	**15.5**
GVI	3.7	**135.5**	**89.3**	1.3	**1.7**
Bright	3.7	**60.2**	**39.6**	0.4	1.6
Wet	**15.4**	29.8	18.1	0.6	**2.6**
NDWI	**8.3**	**83.3**	**41.3**	2.0	0.4
WI	5.9	26.5	12.0	**2.1**	0.9
Inflection.Pt	**11.9**	3.5	1.8	**5.3**	**1.7**
Liquid Water Thickness	**8.2**	-	-	2.0	0.7

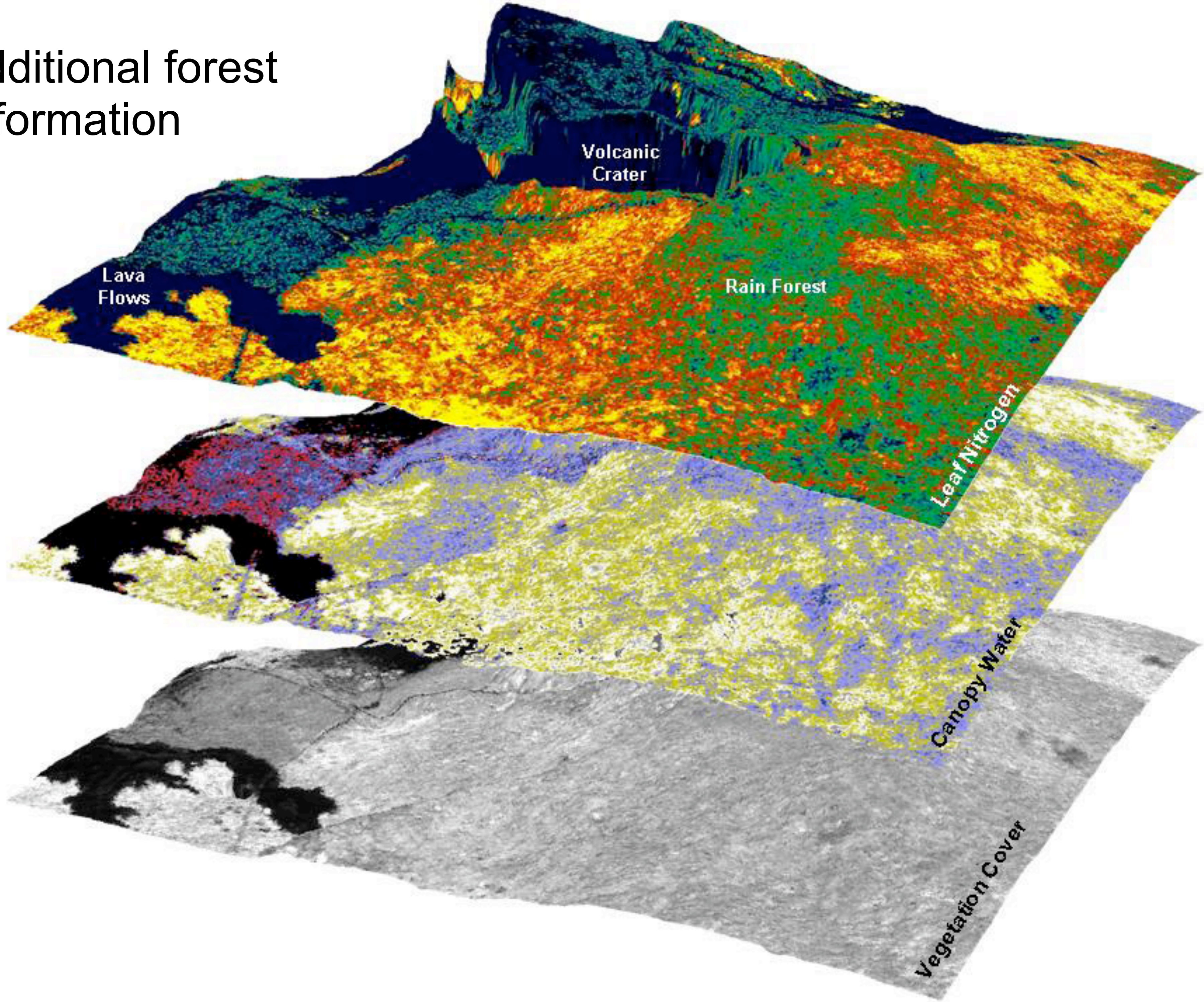
[1] **N Levels 0, 50, 100, 150, 200 kg/ha**

Calculated as the Signal divided by the Noise

High values are good, less than one is bad

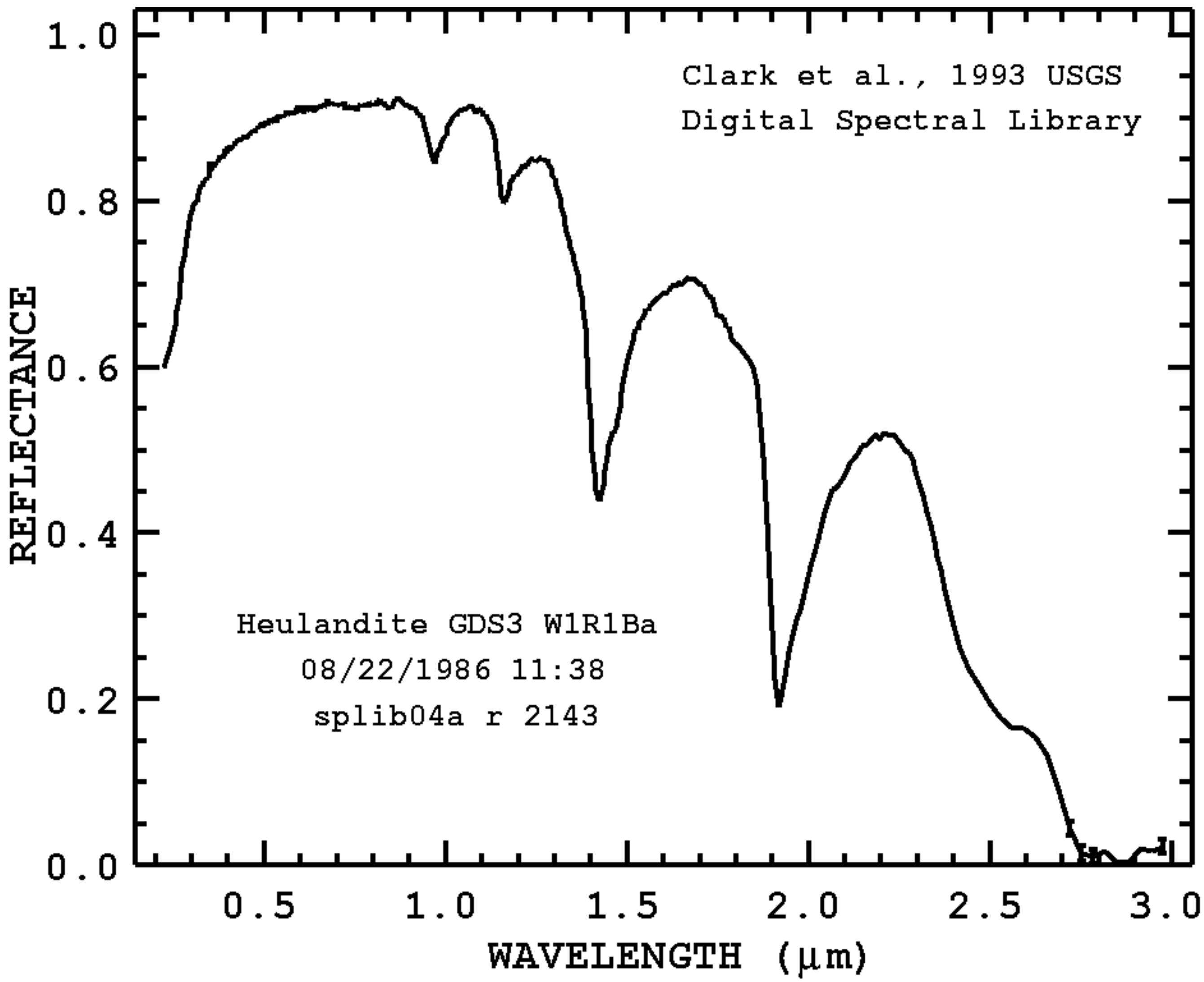
Courtesy of Dar Roberts
UCSB

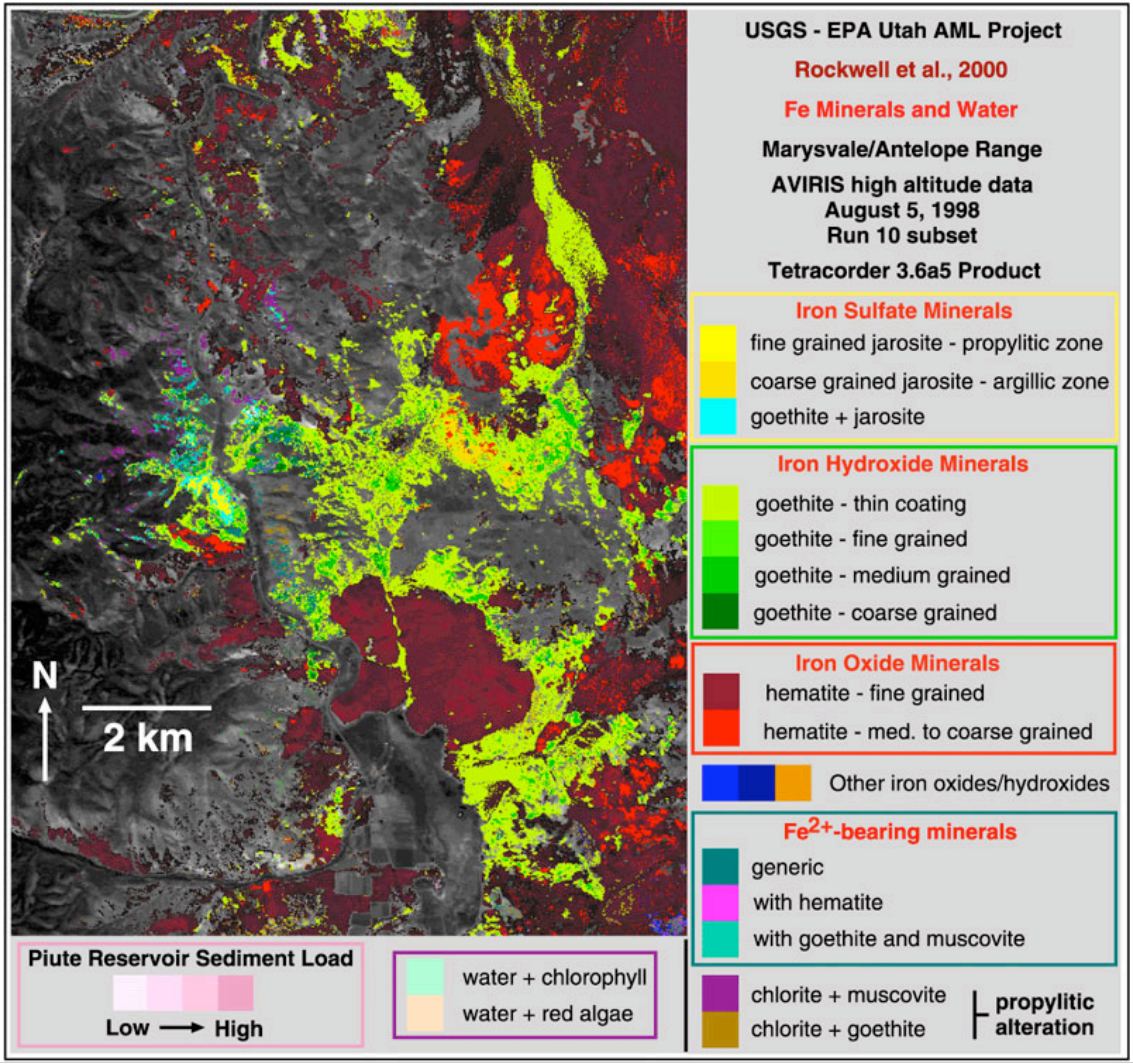
additional forest information



Other applications

Mineral end-members?

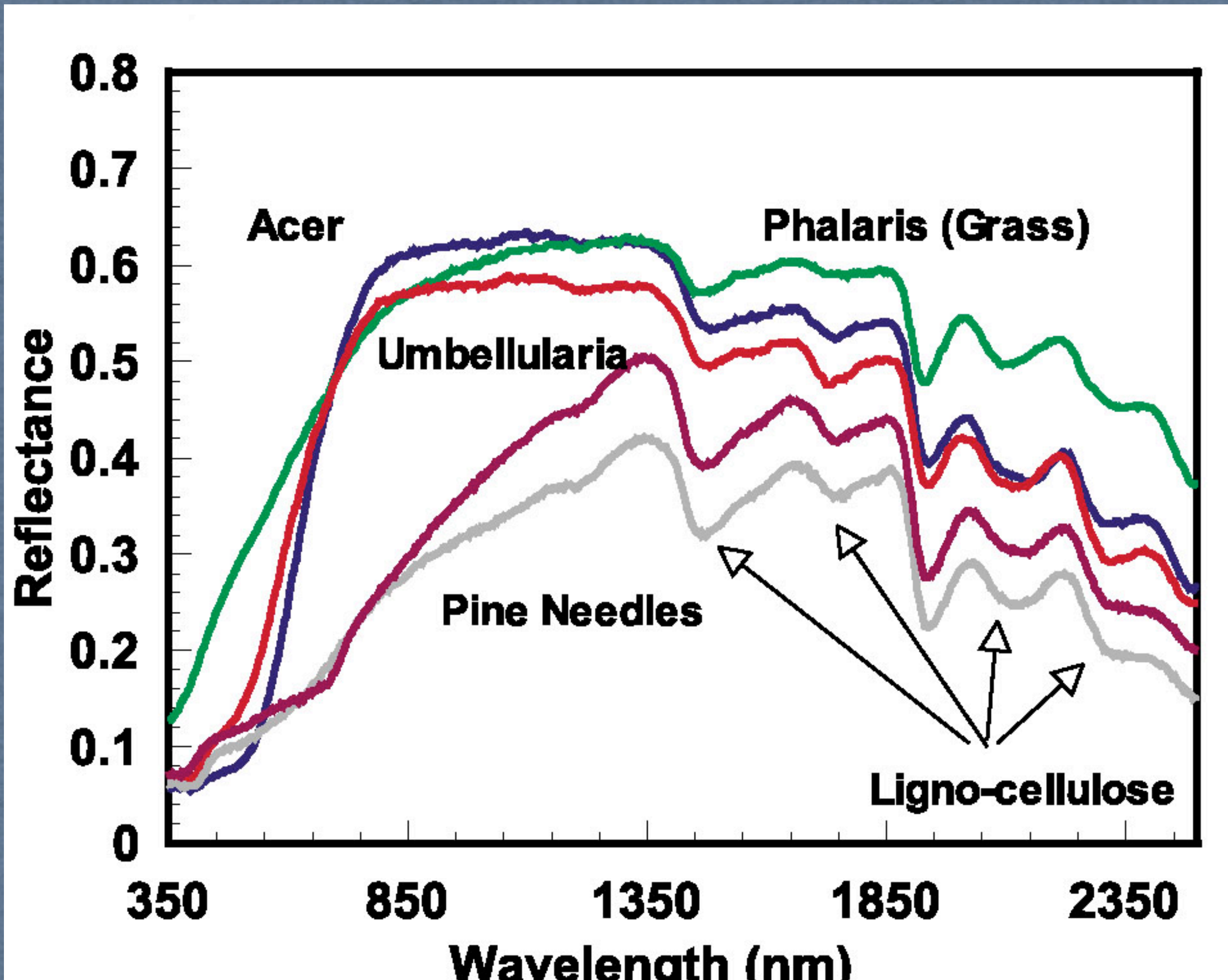


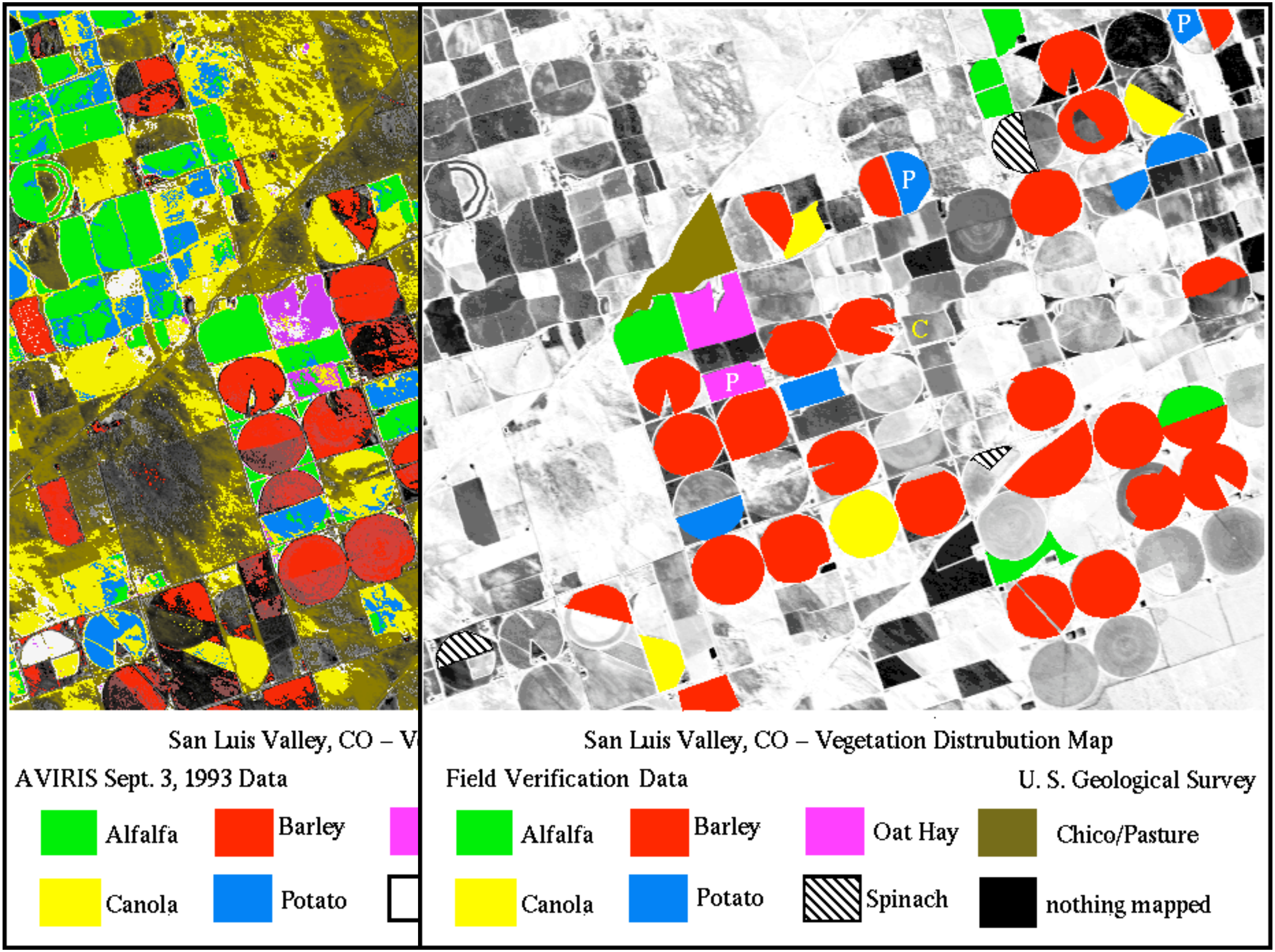


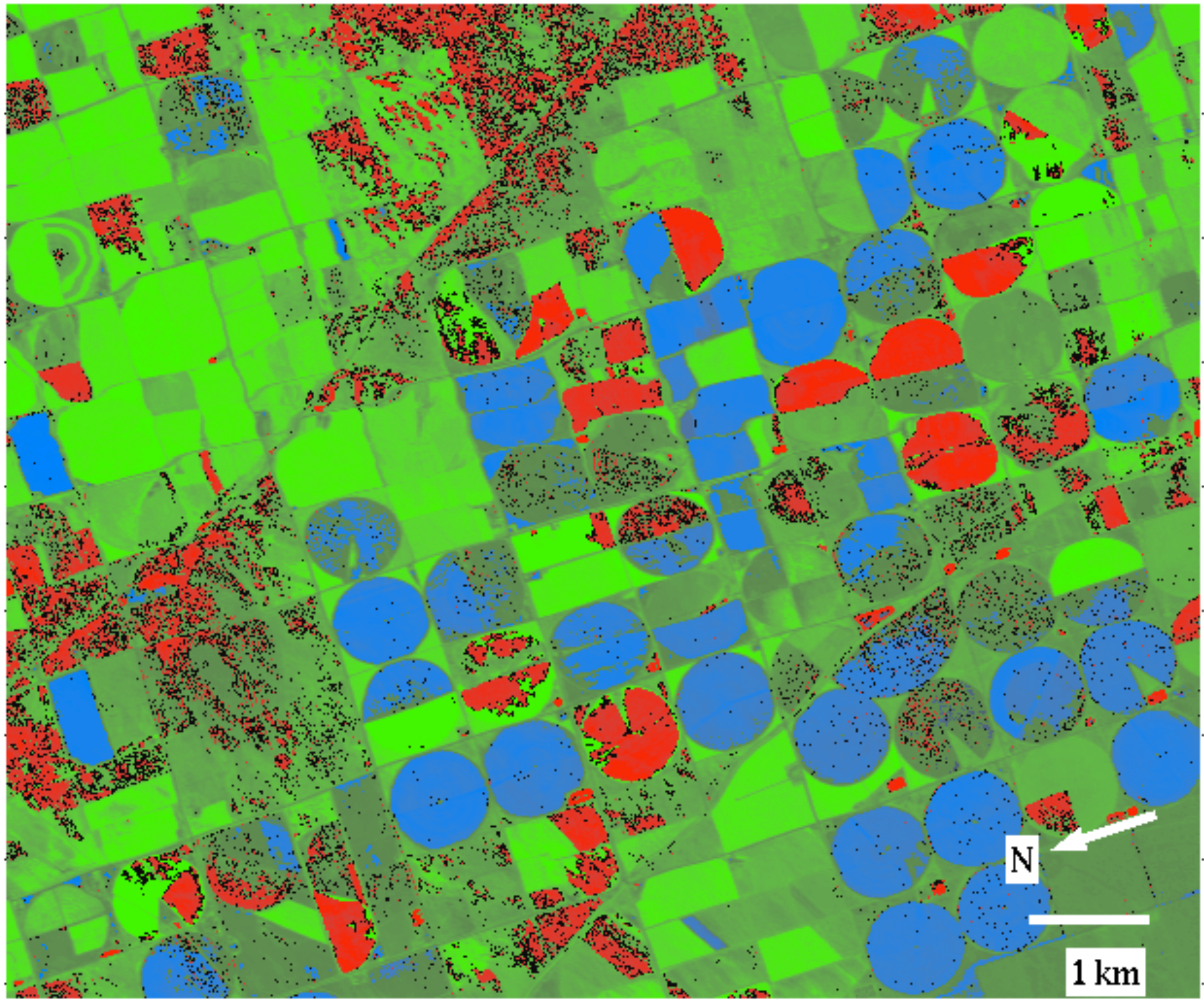
USGS - EPA Utah AML Project
Rockwell et al., 2000
Fe Minerals and Water
Marysvale/Antelope Range
AVIRIS high altitude data
August 5, 1998
Run 10 subset
Tetracorder 3.6a5 Product
Iron Sulfate Minerals
fine grained jarosite - propylitic zone
coarse grained jarosite - argillic zone
goethite + jarosite
Iron Hydroxide Minerals
goethite - thin coating
goethite - fine grained
goethite - medium grained
goethite - coarse grained
Iron Oxide Minerals
hematite - fine grained
hematite - med. to coarse grained
Other iron oxides/hydroxides
Fe^{2+}-bearing minerals
generic
with hematite
with goethite and muscovite
chlorite + muscovite
chlorite + goethite
propylitic alteration
Piute Reservoir Sediment Load
Low → High
water + chlorophyll
water + red algae
N
2 km

Applications

non-photosynthetic vegetation (litter)




P
P
P
C
San Luis Valley, CO –
AVIRIS Sept. 3, 1993 Data
Alfalfa
Barley
Canola
Potato
San Luis Valley, CO – Vegetation Distrubution Map
Field Verification Data
U. S. Geological Survey
Alfalfa
Barley
Oat Hay
Chico/Pasture
Canola
Potato
Spinach
nothing mapped



San Luis Valley, CO – Vegetation Senescence/Stress Map

AVIRIS Sept 3, 1993 Data

U.S. Geological Survey

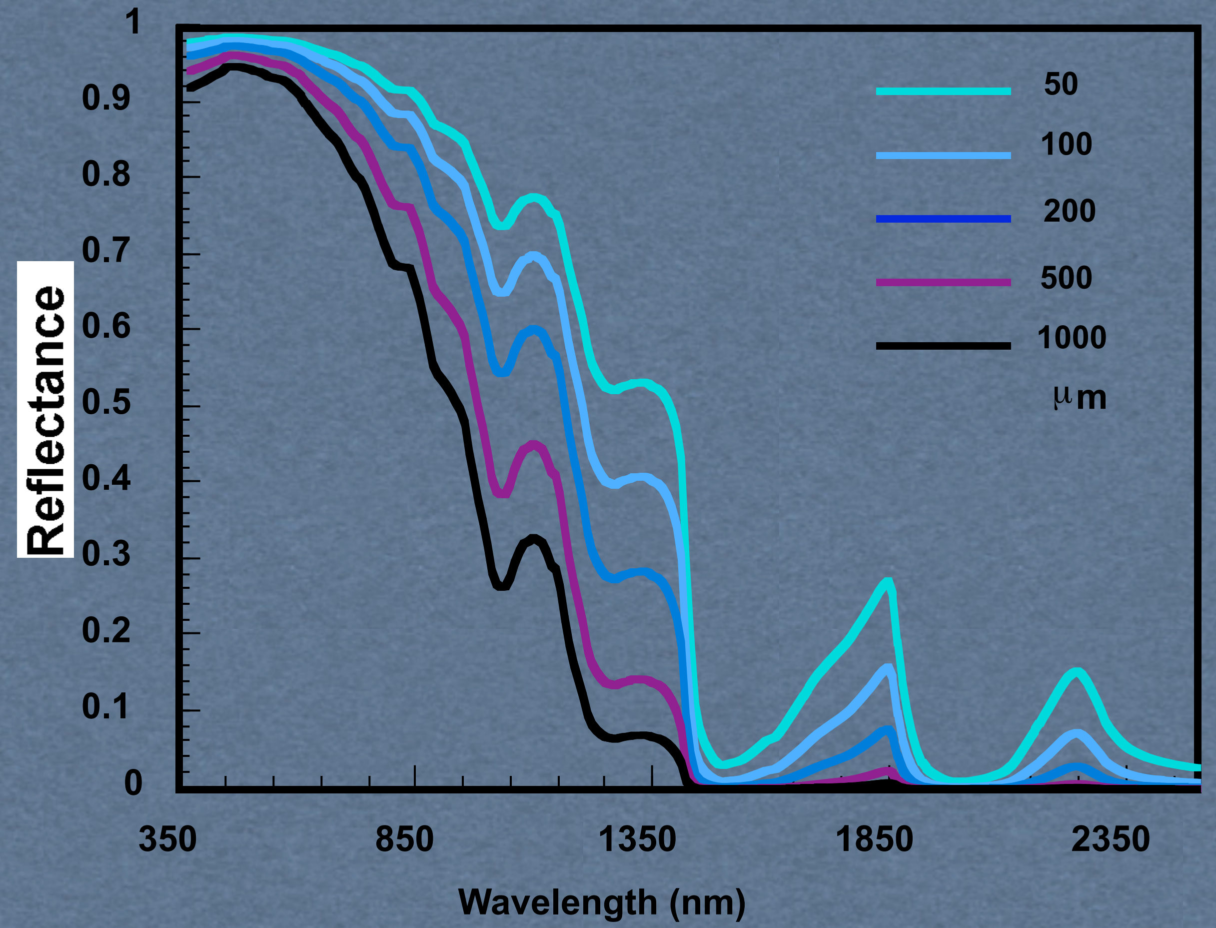
Stressed Vegetation

Green Vegetation

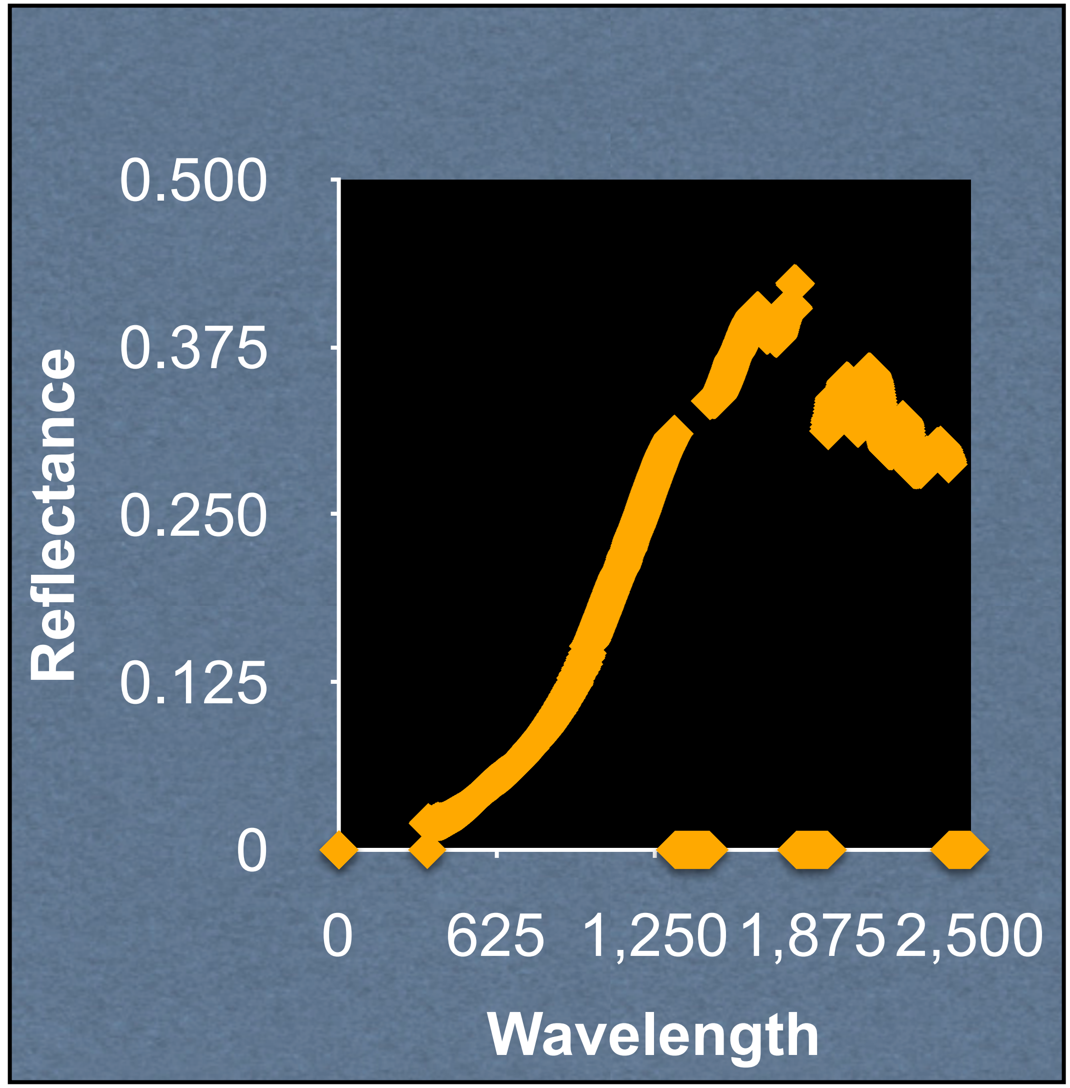
Dry Vegetation and bare ground

Snow Applications

grain size effects on snow reflectance



Gallus gallus (common chicken)



Summary

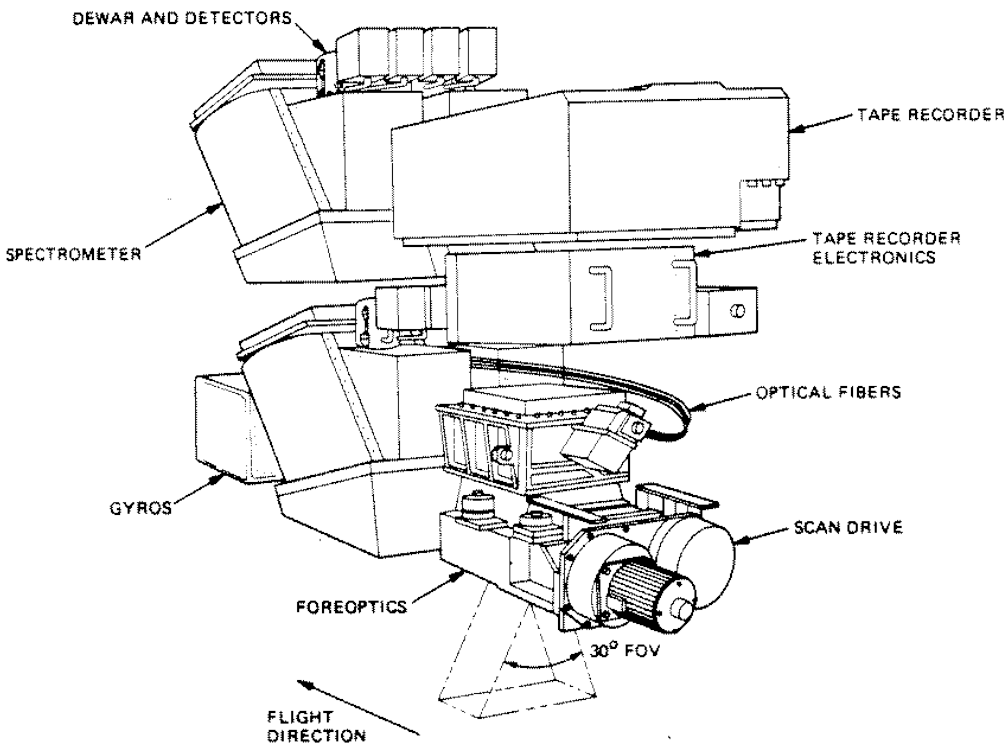
- Imaging spectrometry has broad application for many disciplines
- The strength of imaging spectrometry is in its direct link to physical processes and flexibility
- Imaging spectrometry complements broad band systems, does not compete
- Examples shown here, only reveal a small part of the established potential

Courtesy of Dar Roberts
UCSB

Imaging spectroscopy data sources

data availability for imaging spectroscopy?

- mainly ground and airborne sensors



Airborne Imaging Spectrometers:

Name	Full name	# of Bands	spectral coverage
AVIRIS (JPL)	Airborne Visible/Near Infrard Imaging Spectr	224	400 – 2450 nm
CAESAR (NLR)	CCD Airborne Experimental Scanner for Applications in RS	12	520 – 780 nm
CASI (Itres)	Compact Airborne Spectro-graphic Imager	228	430 – 870 nm
DAIS7915 (DLR)	Digital Airborne Imaging Spectrometer	79	400 – 12000 nm
EPS-A	Environmental Probe System	32	400 – 12000 nm
GERIS	Geophysical & Environmental Research Imaging Spectrometer	63	400 – 2500 nm
HyMap	HyVista Australia	126	450 – 2500 nm

Spaceborne Imaging Spectrometers:

Name	Full name	# of Bands	spectral coverage
ASTER (JPL)	Advanced Spaceborne Thermal Emission & Reflectance Radiometer	14	520 – 11650 nm
MERIS (ESA)	Medium Resolution Imaging Spectrometer	15	400 – 1050 nm
MODIS (NASA)	Moderate Resolution Imaging Spectrometers	36	415 – 14240 nm
SPECTRA (ESA)	Optical & Thermal spectrometer - ESA Earth Explorer Mission - to be launched in 2008 (?) - significant Dutch contribution		400 – 14000 nm

Methods

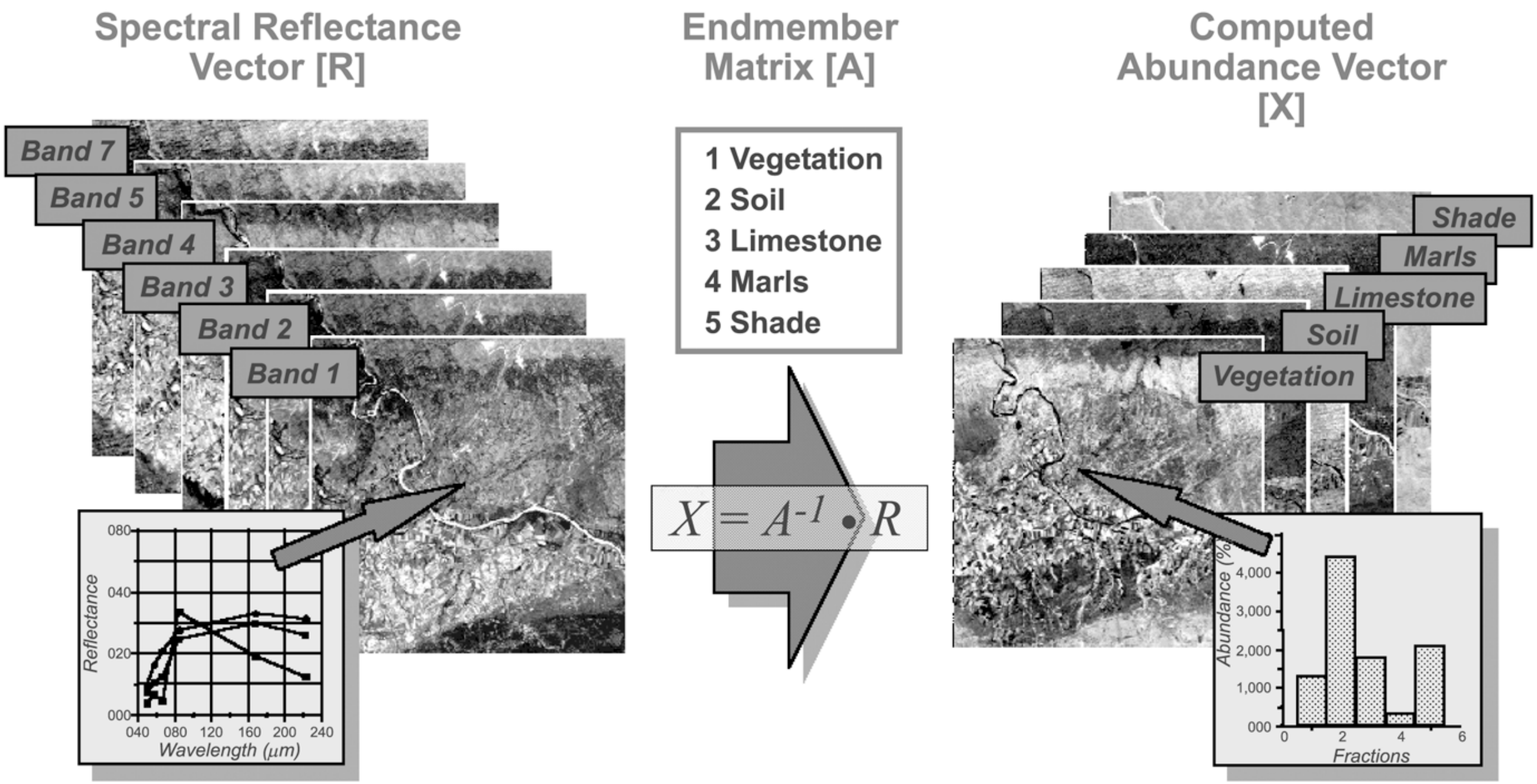
What is mixture modeling?

- hard vs. soft (fuzzy) information extraction
- classification requires that each pixel be given a hard, unambiguous label especially in homogeneous areas (H-resolution)
- in other instances, especially when pixel size is larger than homogenous objects (L-resolution) the land cover is in essence mixture of different land covers
- The purpose of mixture modeling is to estimate the proportion of individual elements (land cover objects) within individual pixels and it is an L-resolution problem.

What is mixture modeling?

- Classification - categorical estimation
  - cookie-cutter model
- Mixture modeling - continuous estimation
  - blender model
- there is improved technology and imagery
- there is increased demand for information such as secondary labels for vegetation
- <u>soft</u> (fuzzy) output maps

Spectral Unmixing



Unmixing accomplished via linear estimation, Supervised learning, or automated approaches

Kinds of mixture modeling

- linear vs. non-linear
- simple vs. probability-based
- supervised vs. unsupervised
- empirical vs. deterministic

Pixel (x,y) as <u>spectral</u> measurement

Band 1 52 DN
Band 2 99 DN
Band 3 13 DN
Band 4 25 DN

data transformation →

Pixel (x,y) as <u>fraction</u> measurement

Endmember A 0.4
Endmember B 0.6

Linear mixture modeling

- It can be assumed that the magnitude of a single photon reflected from the Earth's surface into the sensor field-of-view (pixel) is describable in terms of a simple linear model:

$$r_i = \sum_{j=1}^{n} a_{ij} f_i + e_i$$

we are interested in the inverse of this equation

$\boldsymbol{r_i}$ = reflectance in **i**th spectral band

$\boldsymbol{a_{ij}}$ = reflectance of **j**th end-member in **i**th spectral band

$\boldsymbol{f_j}$ = proportion of end-member **j**

ei = difference between observed and modeled reflectance (error)

IFOV of pixel

a single pixel with three materials: A B and C

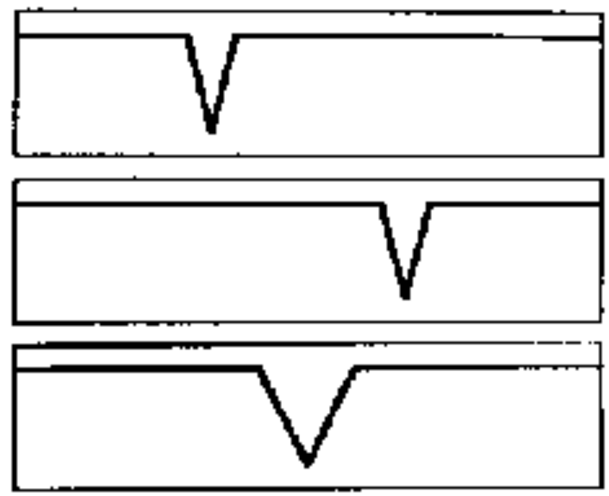
material	fraction
A	0.25
B	0.25
C	0.50

each endmember has a unique spectrum

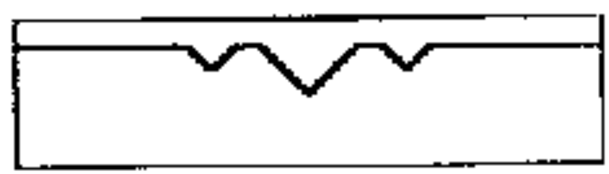
A

B

C



the mixed spectrum is just a weighted average



mix=0.25*A+0.25*B+0.5*C

Linear mixture modeling

- In order for the components (r) to be computed, the number of end-members must be less than the number of spectral bands
- This model simply expresses the fact that the integrated signal (r) received at sensor in a given band will be a linear sum of all individual signals from individual land cover types
- The constraint specifies that the individual fractions must take values between 0 and 100 percent and that the fractions for any given mixed pixel must sum to 100 percent or less.

What are end-members?

- End-member refers to spectral phenomena where the pure form of the category of interest (green leaves, soils, shade, water etc...)
- End-members are spectral only, and do not represent materials although spectra may represent materials
- End-members in an image refer to pixels (or locations) whose reflectance value corresponds to the reflectance value of the pure spectral sample
- These end-members correspond to the materials with spectra that combine linearly to produce all of the spectra in the image

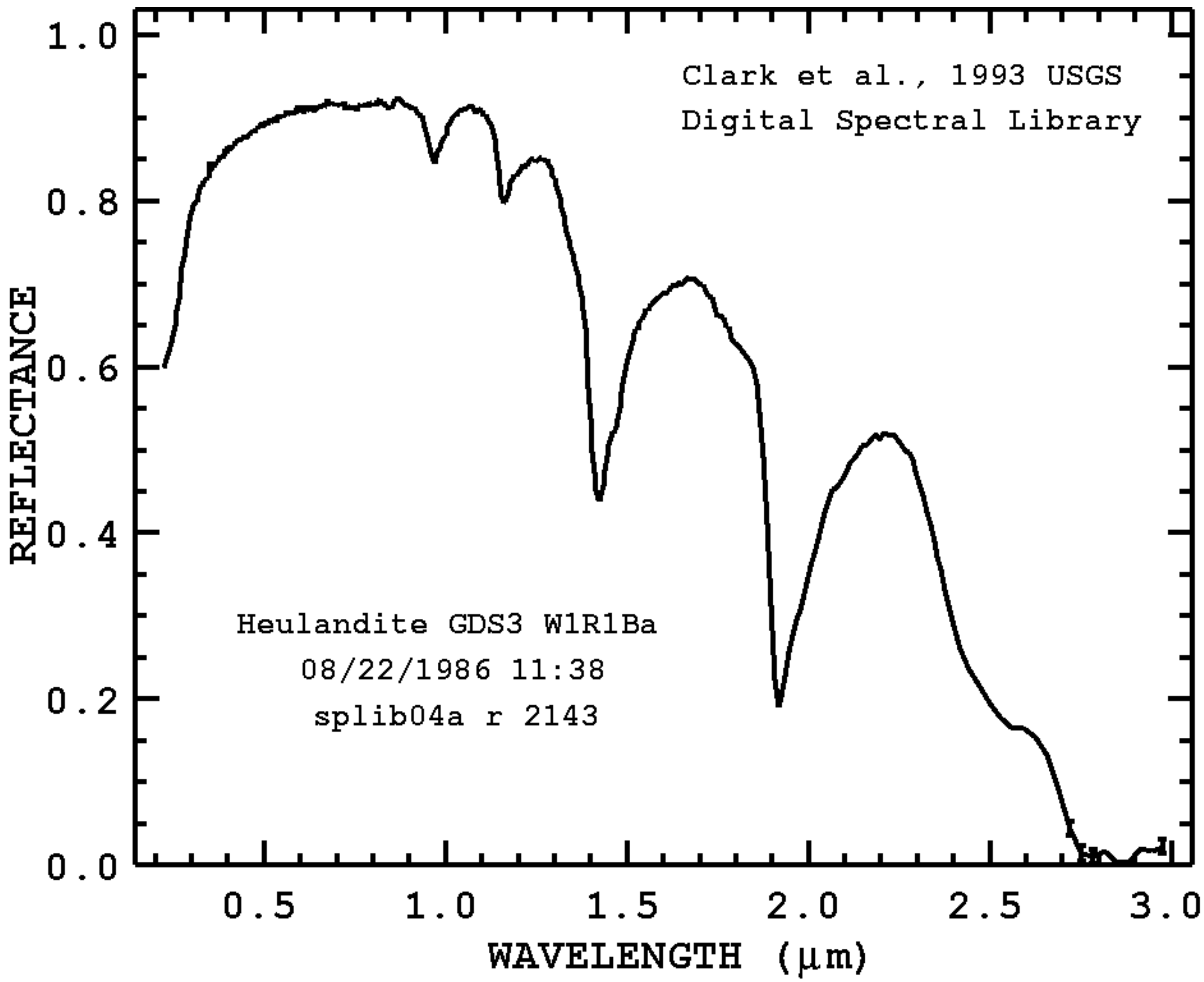
How do we obtain end-members?

- spectroscopic library matching
  - make own in-situ observations
  - NASA-JPL spectral library

    http://speclib.jpl.nasa.gov/
  - USGS spectral library

    http://speclab.cr.usgs.gov/ spectral.lib04/spectral-lib04.html
- empirical approach
  - extract from imagery at hand
  - extract from another imagery
- probabilistic approach

How do we obtain end-members?



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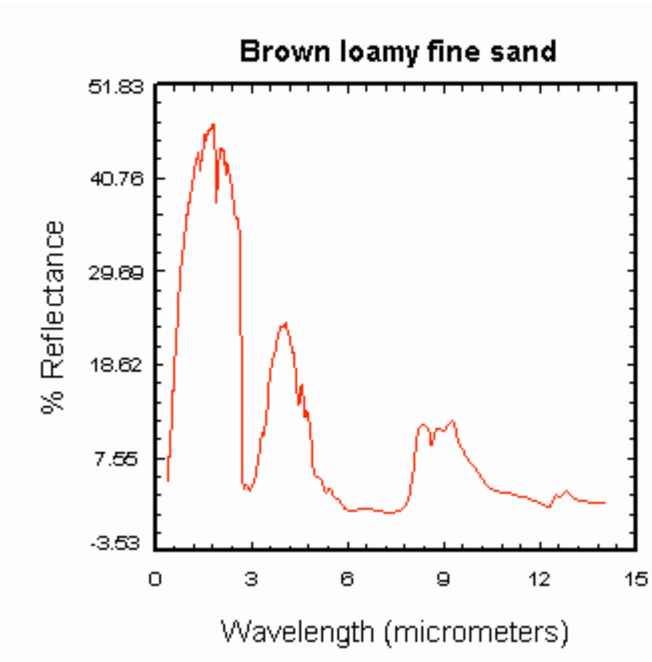

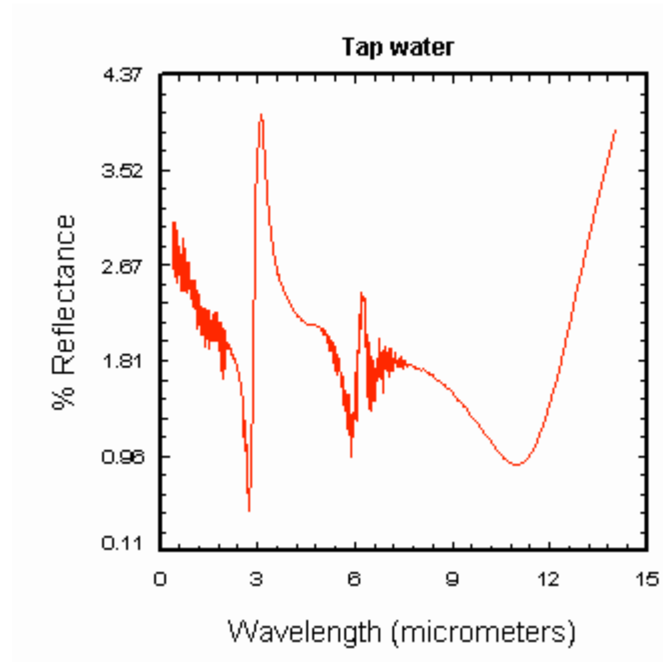

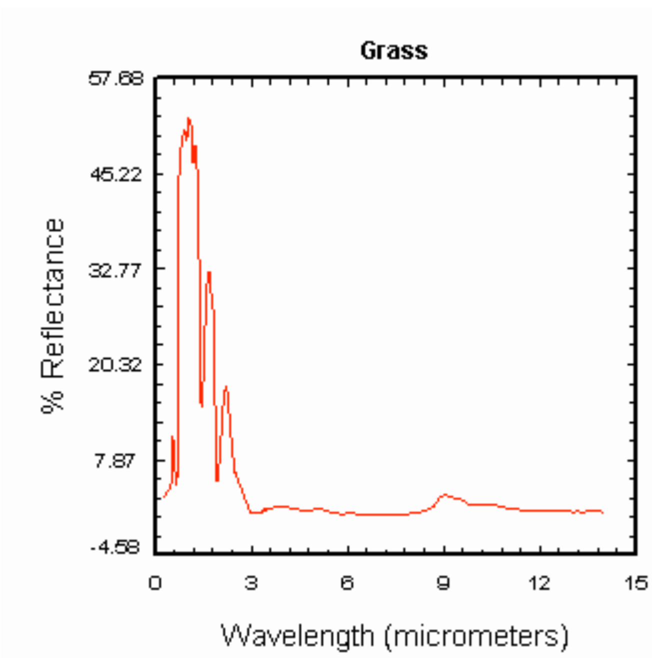

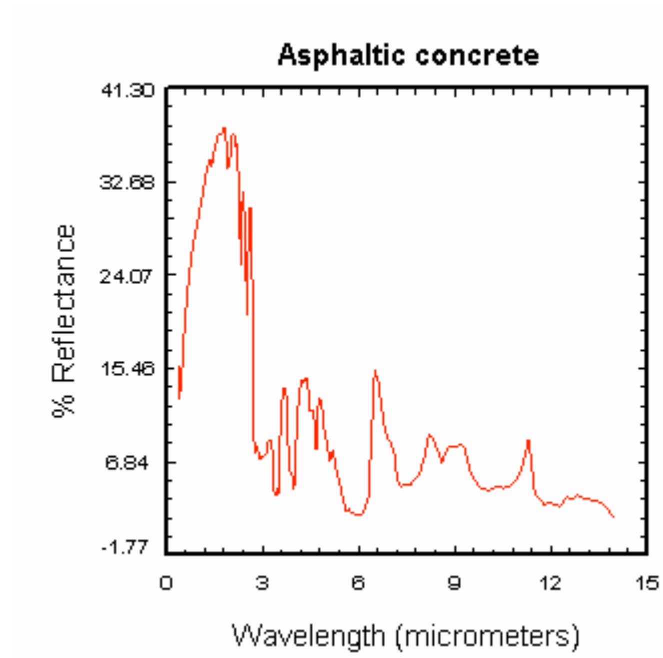

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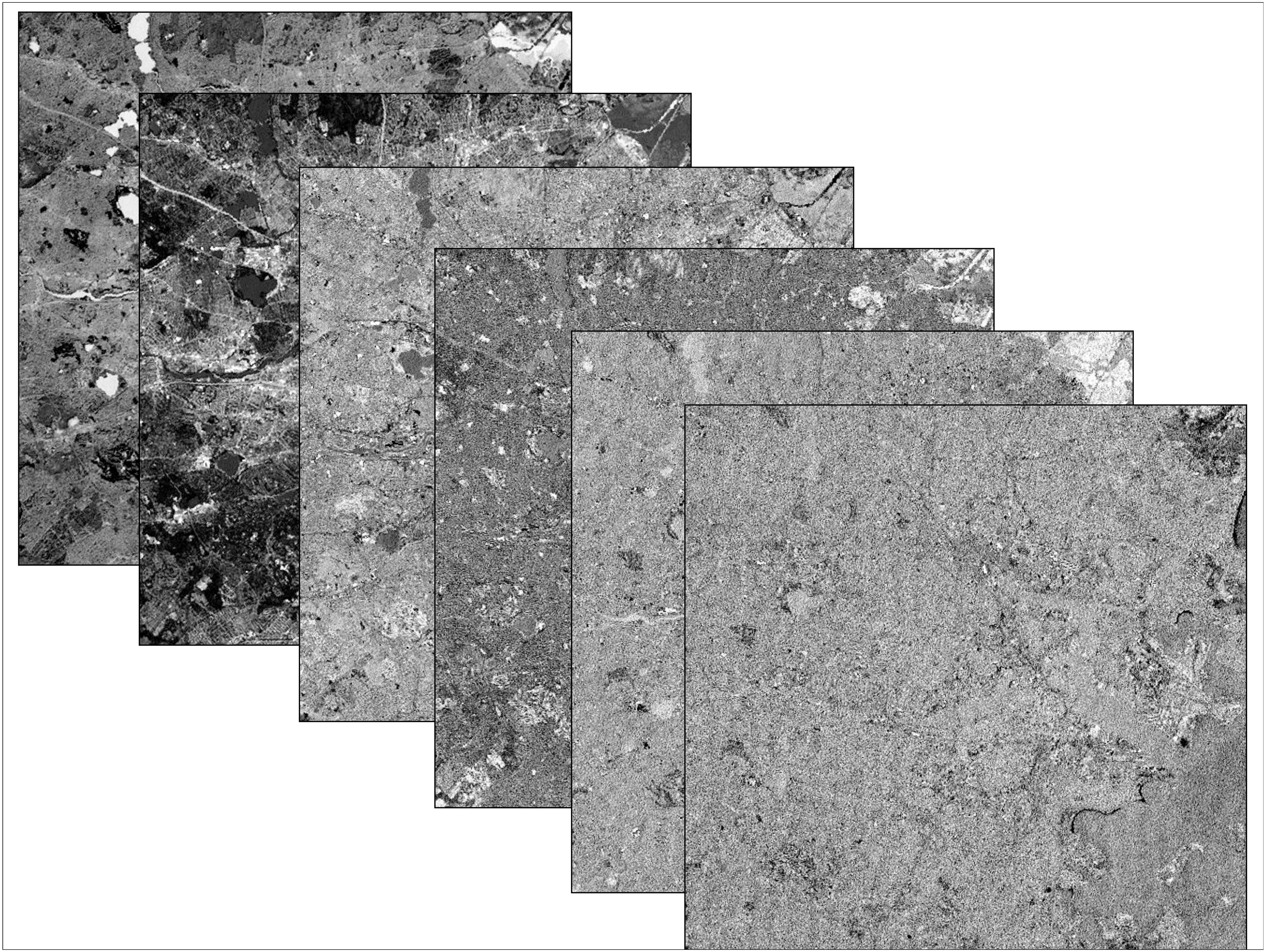
- empirical approach
  - extract from imagery at hand
  - extract from another imagery
- probabilistic approach

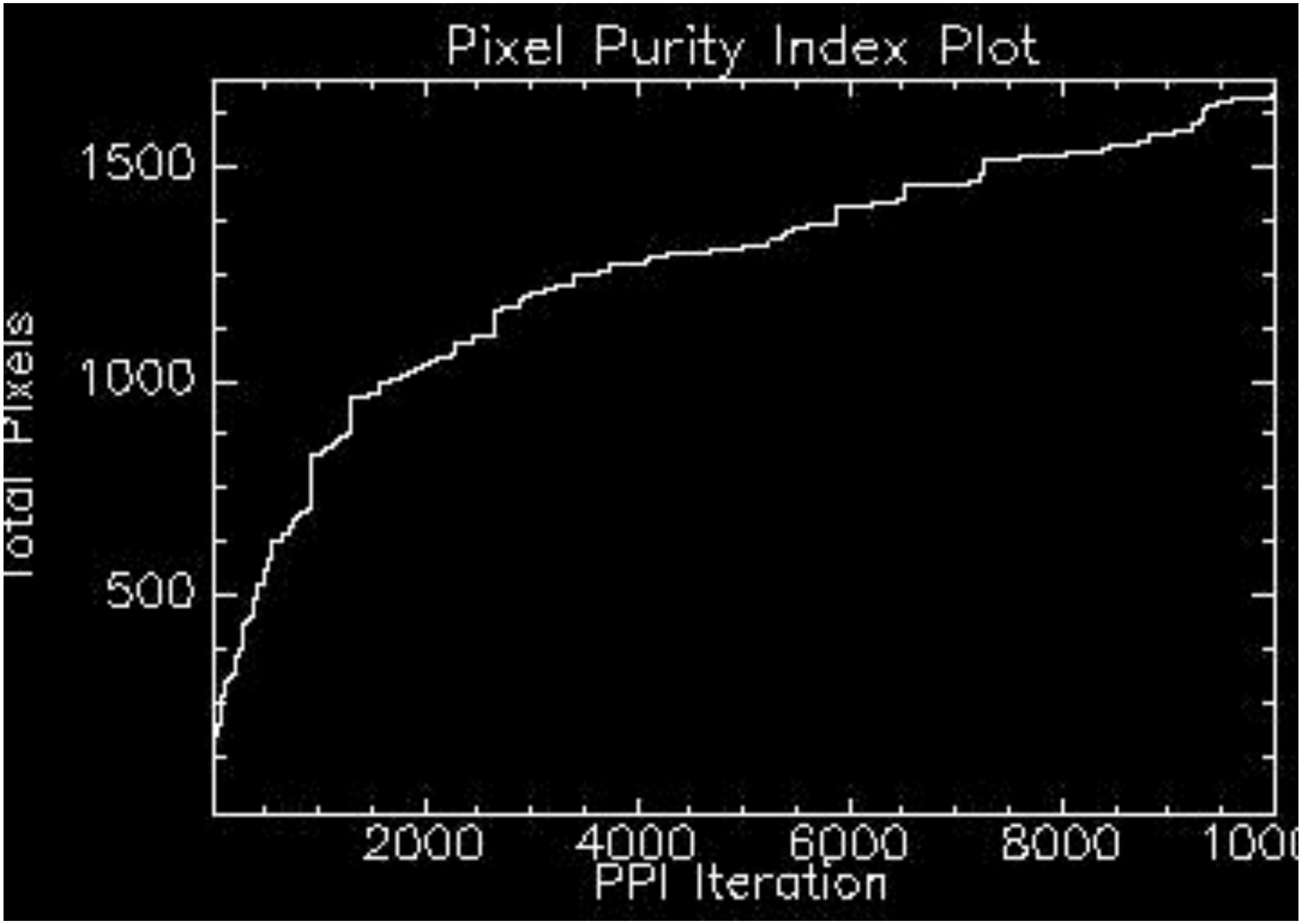
How do we obtain end-members?

- Pixel Purity Index (PPI)
  - Sometimes, it is difficult to locate end-members because only a few pixels contain pure samples
  - PPI is a rigorous mathematical method to repeatedly project n-dimensional scatterplots to 2-D space and marking the extreme pixels
  - Each time spectral data is projected, we can note the the most extreme (pure) pixels and simply keep track of the number of times a pixel is considered extreme to make PPI image

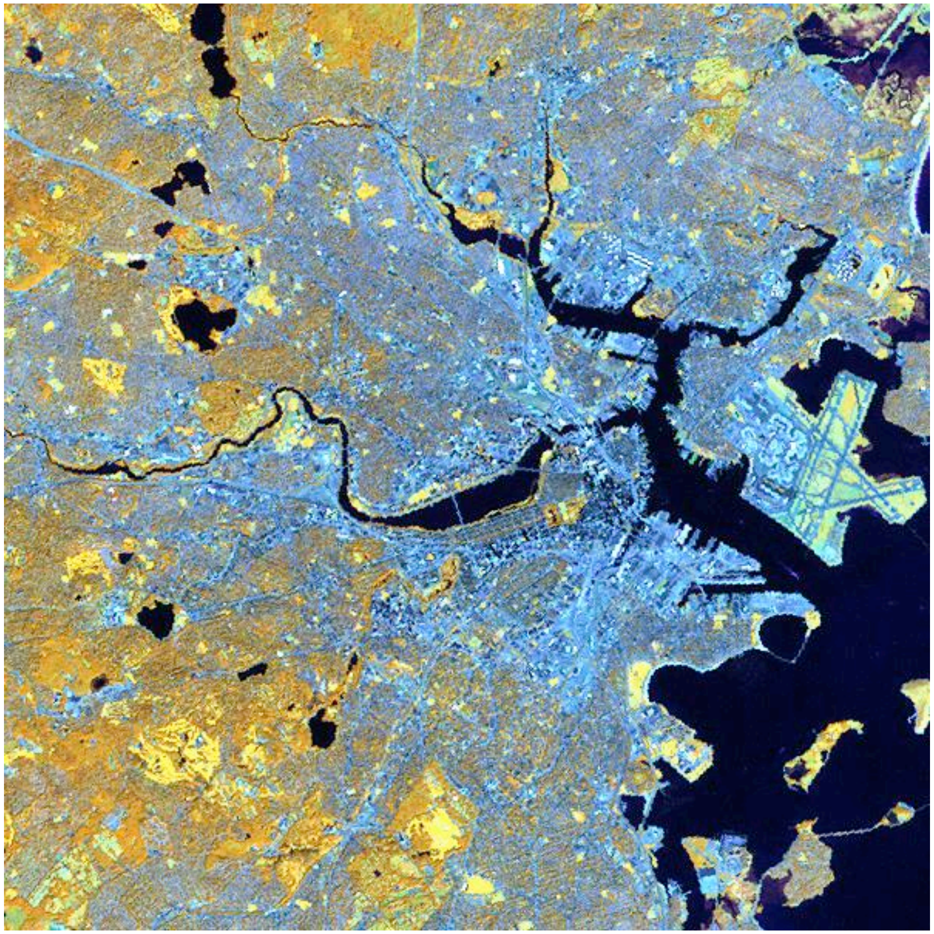
How do we obtain end-members?

- MNF
  - used to reduce dimensionality and therefore noise in the image data set
  - it is a cascaded PCA analysis approach
  - the first de-correlates and scales noise in the data
  - the second creates MNF eigen images (i.e. PCA)
  - use these images in PPI analysis



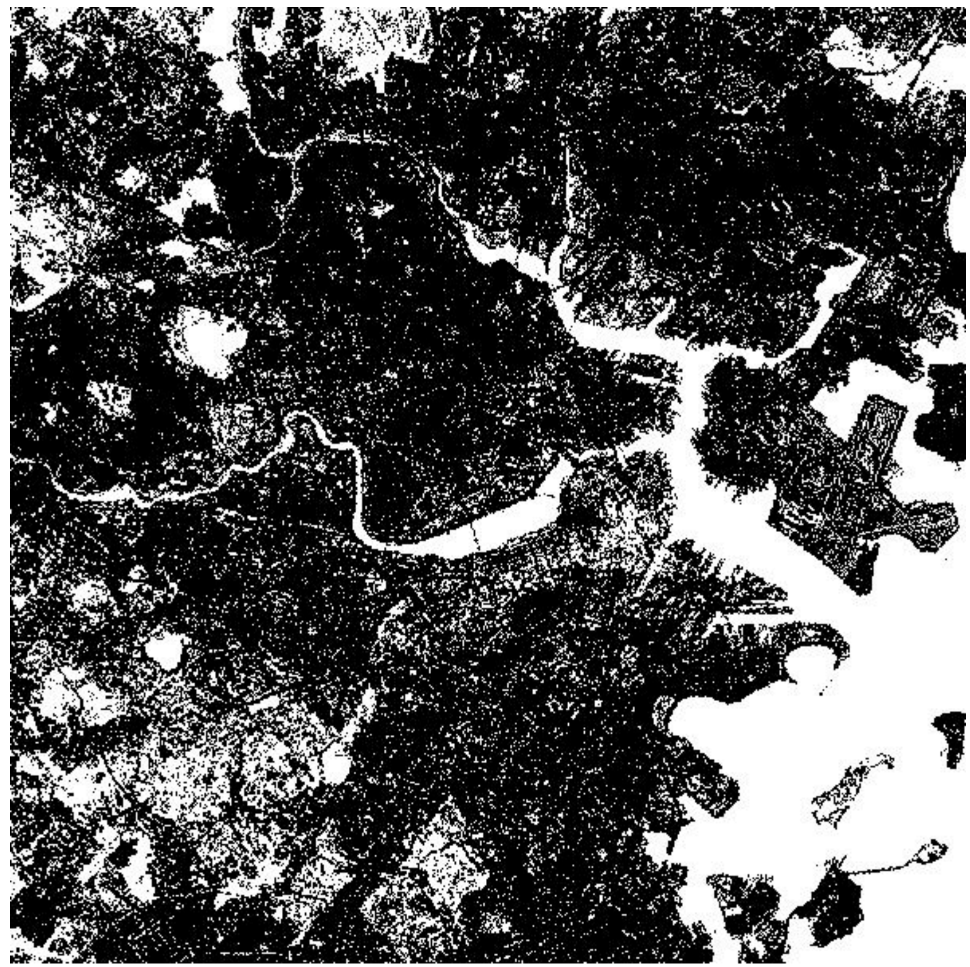


Boston image number of pure pixels after 10,000 iterations



Boston 453 as RGB

Boston PPI image



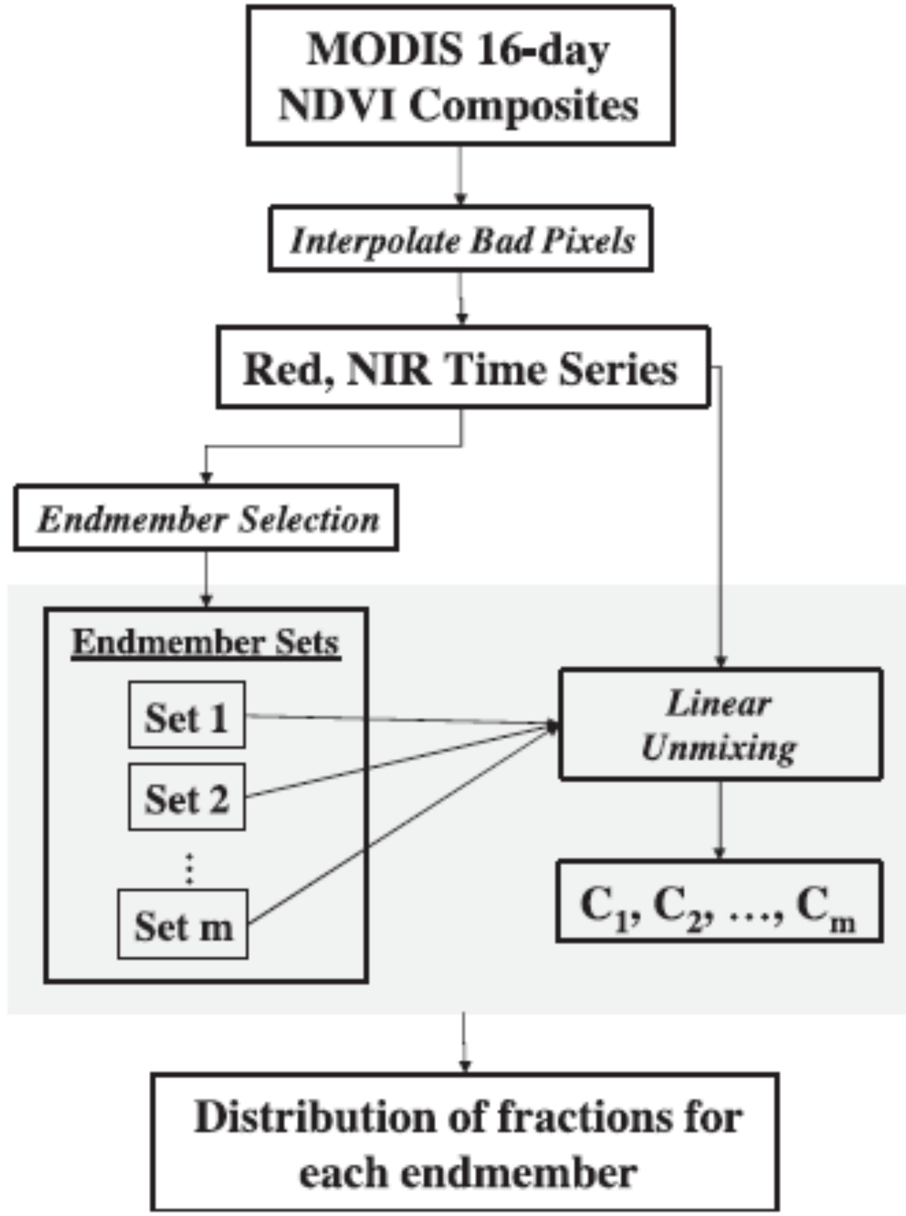
Issues in mixture modeling

- bad (non-pure) end-member choice
- end-member variability
- fraction overflow
- omitted mixture component (missing important land cover category)
- data may not be able to describe the mixtures
- reflected photon into the sensor pixel has multiple interactions wit other surface objects
- non-linear relationships

probabilistic approach

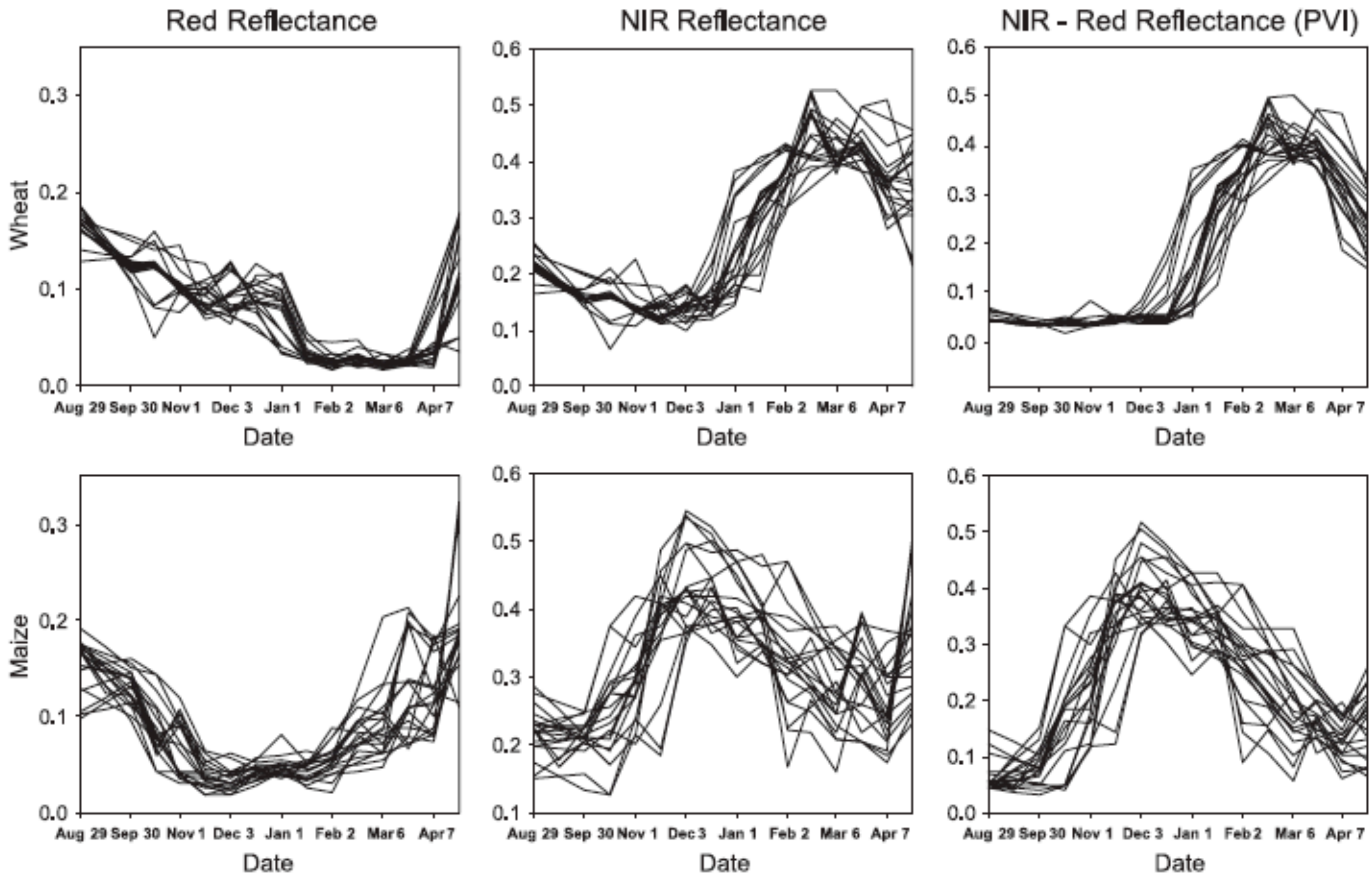
- Linear mixture models assume that the end-member spectra are known exactly for each pixel
- In reality, however, reflectance is likely to vary across space and time, even for a narrowly defined end-members
- So, rather than define end-members with a single spectrum, it is possible to define end-members as a set of spectra which represent the full range of potential variability
- Thus, end-member fractions are not estimated as single values, but rather as a probability distribution that can be used to construct confidence intervals appropriate to the desired application

probabilistic approach



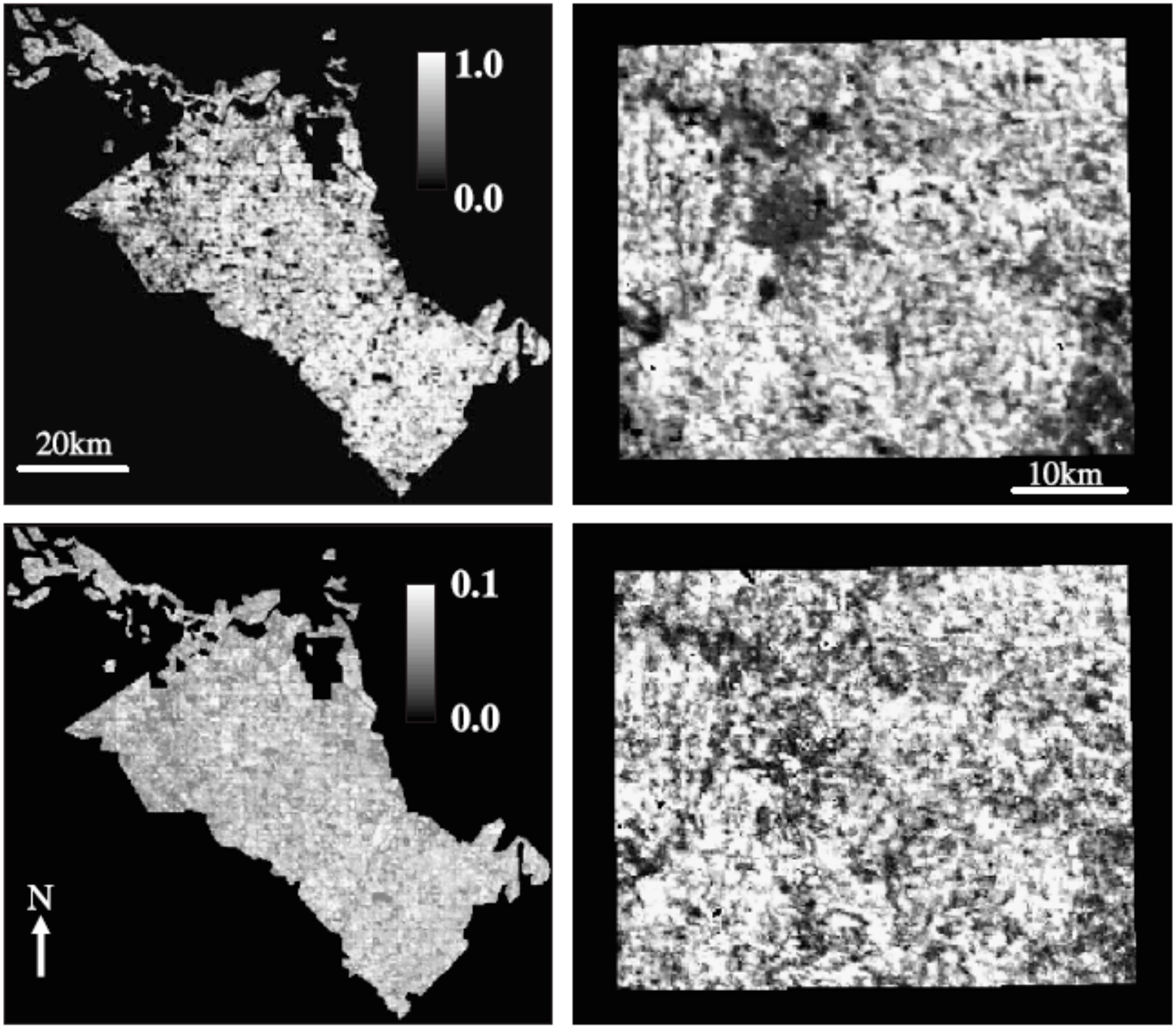
Lobell and Asner (2004)

probabilistic approach



Lobell and Asner (2004)

probabilistic approach



mean image

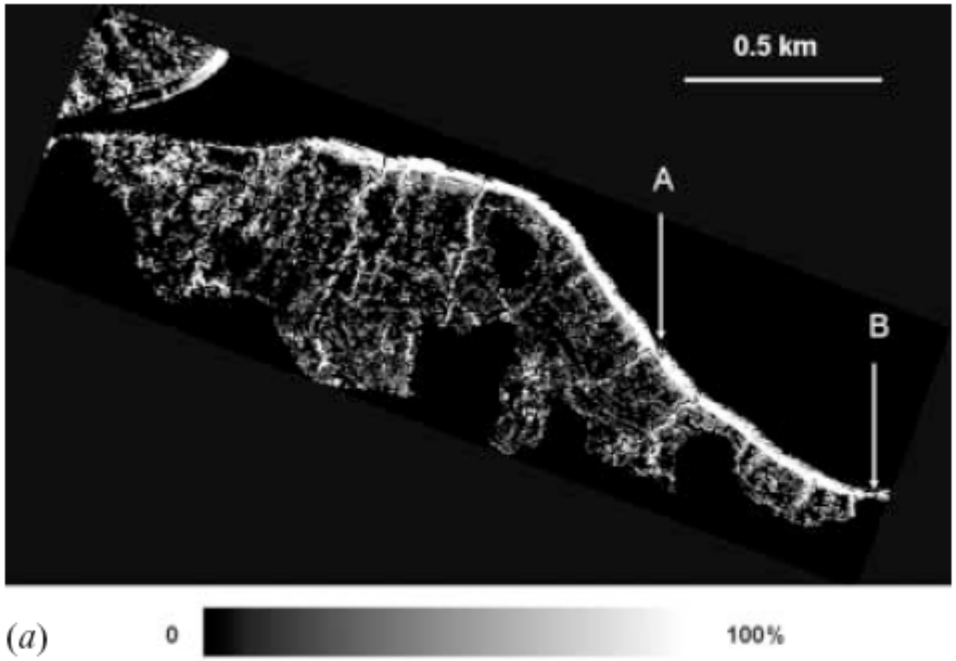
standard deviation image

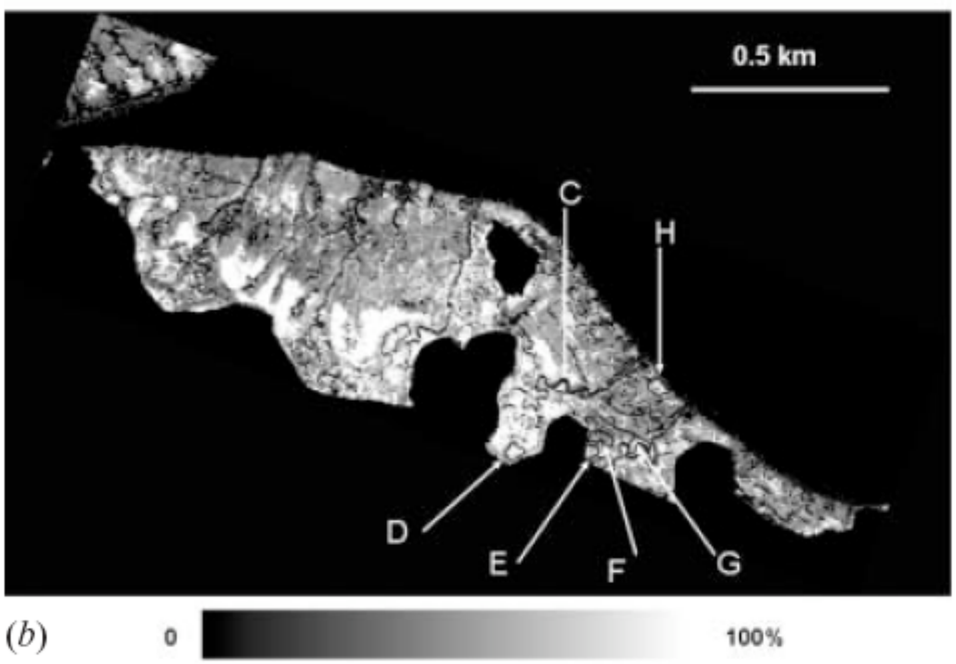
Lobell and Asner (2004)

Multi-endmember spectral mixture analysis (MESMA)

- Given the variation in the number of endmembers needed for optimal unmixing, the use of a fixed suite of endmembers can cause large errors in the estimated fractional cover
- MESMA assumes that although an image contains a large number of spectrally distinct components, individual pixels contain a limited subset of these
- MESMA decomposes each pixel using different combinations of possible endmembers, allowing a large number of endmembers to be utilized across a scene and the optimization of endmembers for individual pixels.

Roberts et al (1998)





Fraction images of two different salt marshes found in the San Francisco Bay area developed by applying the MESMA method to airborne AVIRIS images

Li et al (2005)

Spectral Angle Mapper (SAM)

- Spectral angle mapping is based on the well-known coefficient of proportional similarity, or cosine-theta approach
- This index defines that the degree of similarity between two objects (spectra in this case) may be evaluated in relation to the proportions of their presence
- For any two spectra, the index is determined from cosine theta which is merely the cosine of the angle between the two row vectors as situated in n-dimensional space
- The index value of 0 means the two spectra are completely dissimilar and index value of +1 means the two spectra coincide

Spectral Angle Mapper (SAM)

$$\cos\theta = \frac{\sum_{i=1}^{N} r_i p_i}{\left(\sum_{i=1}^{N} r_i^2\right)^{0.5} \left(\sum_{i=1}^{N} p_i^2\right)^{0.5}}$$

ri - reference pixel vector

pi - any other image pixel vector