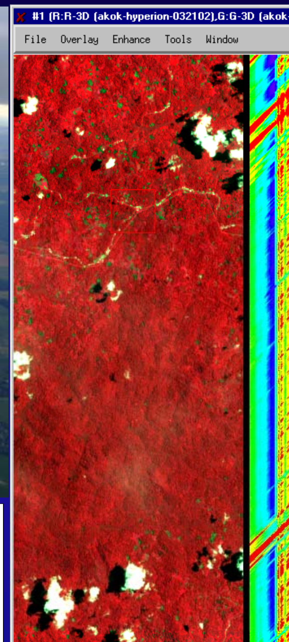
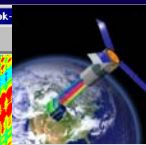
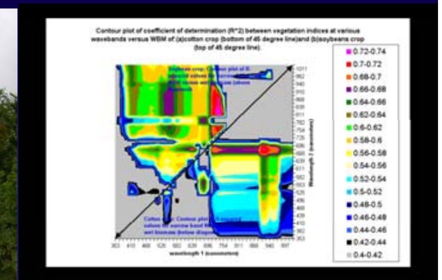
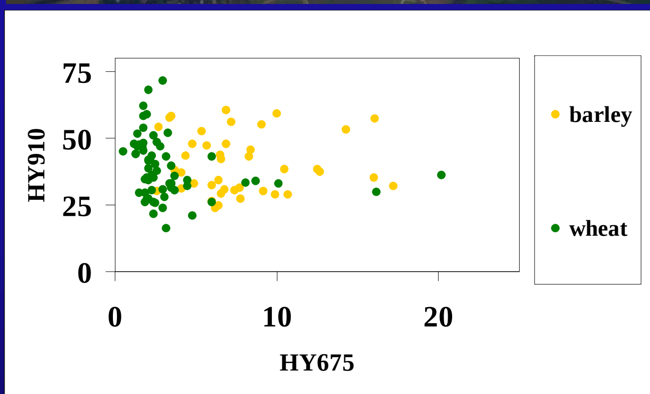
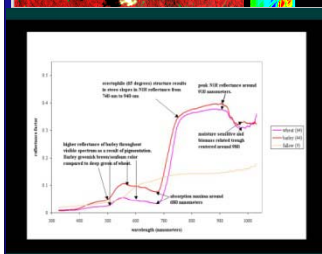
Advanced Hyperspectral Remote sensing of the Terrestrial Environment

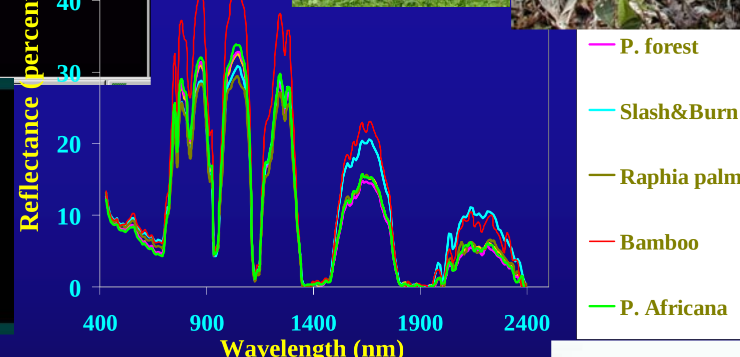












Prasad S. Thenkabail[1], Dean Riley[2], and John G. Lyon[3],

1= Research Geographer, U.S. Geological Survey (USGS); 2 = Aerospace Corporation; 3 = Clifton, VA

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Workshop # 7: Advanced Hyperspectral Sensing of the Terrestrial Environment,
Pecora 18, Herndon, VA. November 13-18, 2011

Today's Course Structure

WS 7

Advanced Hyperspectral Sensing of the Terrestrial Environment

Prasad Thenkabail, *U.S. Geological Survey*
Dean Riley, *The Aerospace Corporation*
John Lyon, *U.S. Bureau of Land Management*

****

Course Structure

1. **Advanced Hyperspectral Remote Sensing of the Terrestrial Environment: Data Characterisitcs and Data Mining:** Prasad S. Thenkabail and John G. Lyon (70 min + 10 min questions)

2. **Advanced Hyperspectral Remote Sensing of the Terrestrial Environment: Methods of Modeling and Mapping:** Prasad S. Thenkabail and John G. Lyon (70 min + 10 min questions)

Break (20 min)

3. **Hyperspectral Thermal Infrared Remote Sensing of Geological and Environmental Applications:** Dean Riley and John Lyon (70 min + 10 min questions)

4. **The big picture: Applications-driven question and answer period , driving decision-making for societal benefit:** John Lyon, Dean Riley, Prasad S. Thenkabail (40 min questions)

****

ADVANCED WORKSHOP

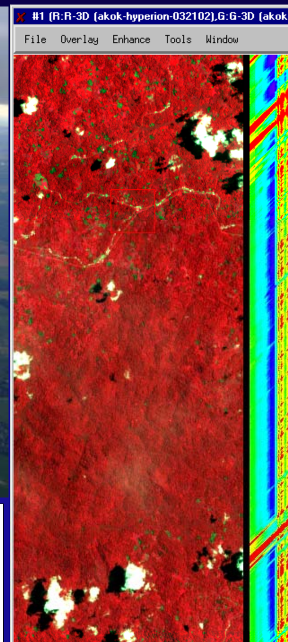
Hyperspectral sensing has created a wealth of opportunity to understand our changing world. It is now incumbent to focus on applications and best methods to derive true productivity. The instructors will share their deep knowledge on important economic themes of the terrestrial environment domestically and internationally. The issues of vegetation, croplands, geological and mineral exploration, and coastal/wetland applications hold great import in our growing and increasingly commodity driven world. These applications derive needed information and power decision making through current paradigms of sustainability, Food and Water Security, nation building through resource management, coastal and marine spatial planning, and so forth. Attendees should have some knowledge and bring their own applications questions for attention during and at the end of the Workshop.

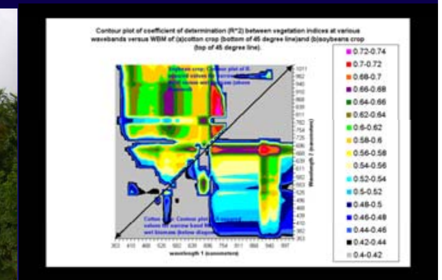
I. Overview of Advanced Hyperspectral Remote Sensing
II. Hyperspectral Sensing of Vegetation and Croplands
III. Hyperspectral Sensing of Geology and Mineral Deposits
IV. Hyperspectral Sensing of Wetlands and Coastal Regions
V. The Big Picture: Driving Decision-making for Societal Benefit
VI. Applications-driven Question and Answer Period

Advanced Hyperspectral Remote sensing of the Terrestrial Environment

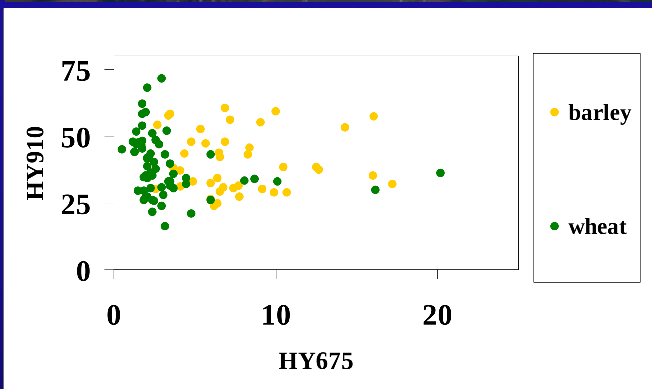
Lecture # 1: Data Characteristics and Data Mining

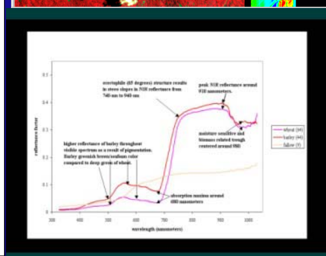
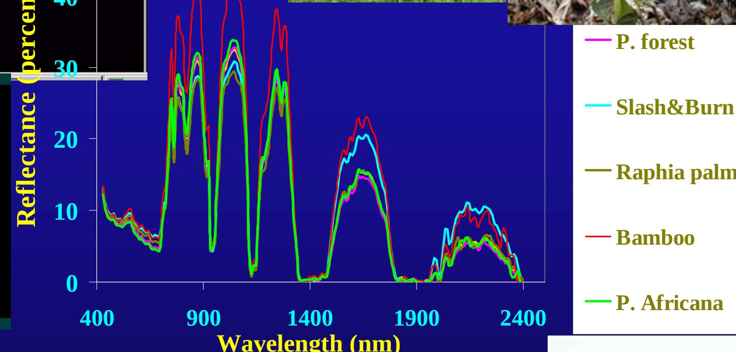












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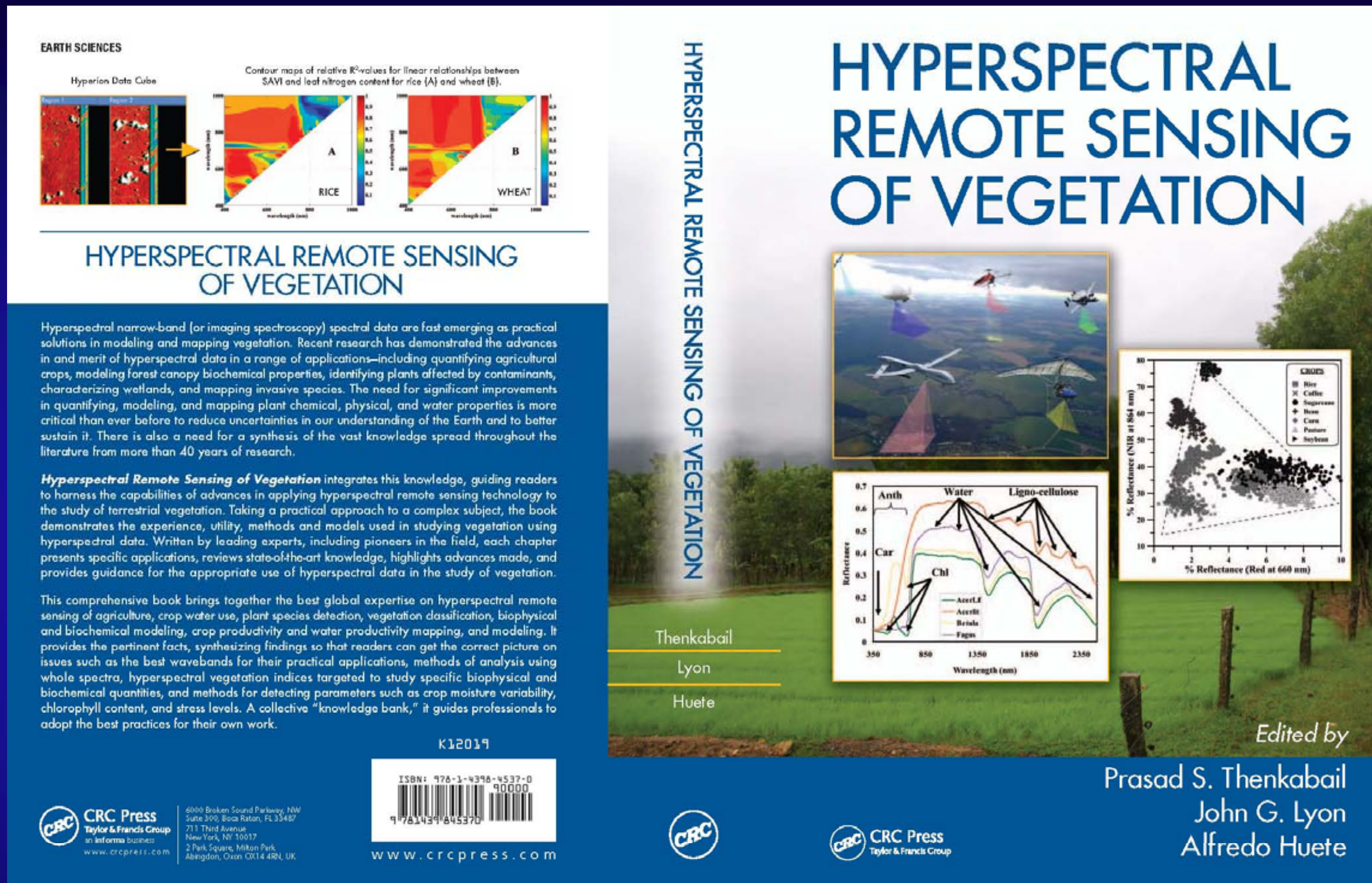
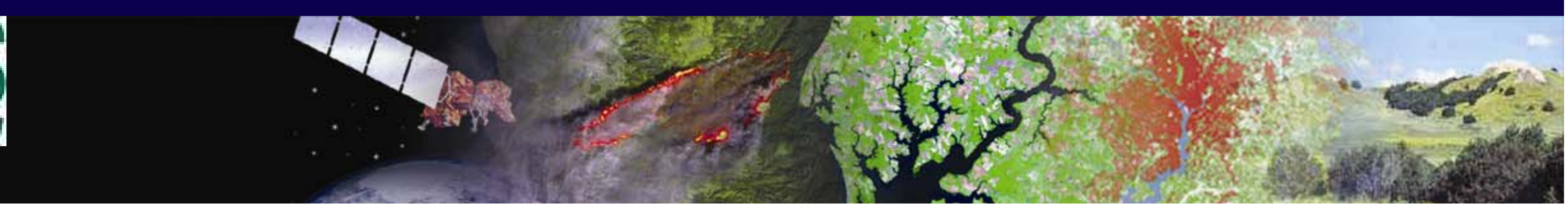
Hyperspectral Remote Sensing Vegetation

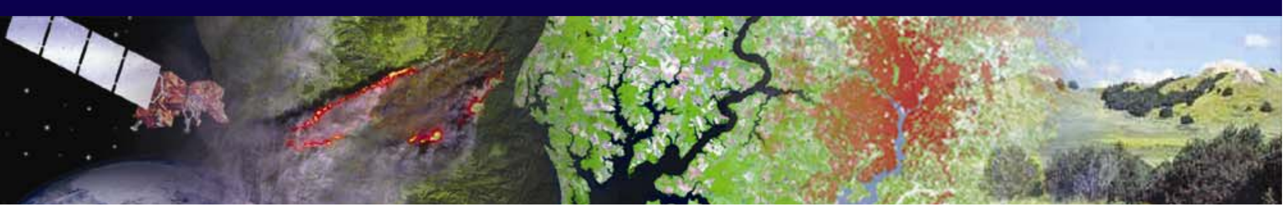
References Pertaining to this Presentation



Thenkabail, P.S., Lyon, G.J., and Huete, A. 2011. Book entitled: "Advanced Hyperspectral Remote Sensing of Terrestrial Environment". 28 Chapters. CRC Press- Taylor and Francis group, Boca Raton, London, New York. Pp. 781 (80+ pages in color).

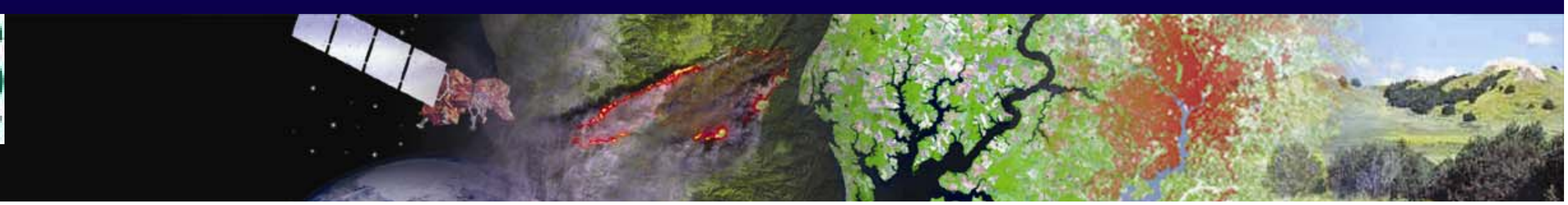


Overview of
Today's Lecture



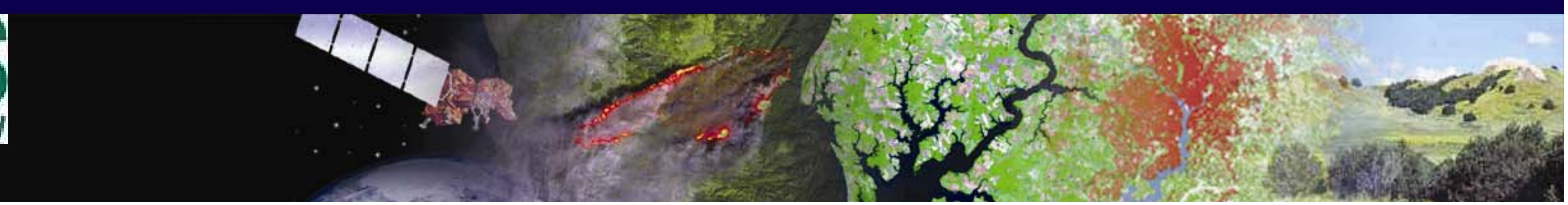
Overview of Today’s Lecture

1. **Importance and definitions:** hyperspectral remote sensing (imaging spectroscopy) of vegetation;
2. **Sensor Systems**: ground-based, truck-mounted, airborne, spaceborne;
3. **Hugh’s phenomenon, data redundancy and data mining:** strategies to overcome data redundancy;
4. **Characteristics:** of hyperspectral data on vegetation
5. **Mega file data cube (MFDC):** composing hyperspectral data;
6. **Acquiring hyperspectral data:** approaches and techniques;

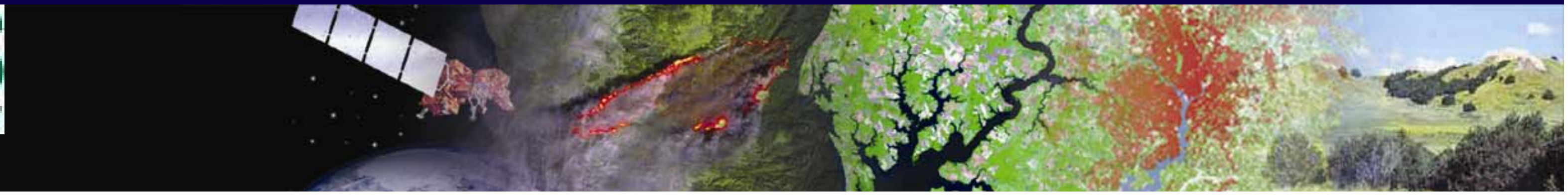


Overview of Today's Lecture

4. **Methods of modeling and mapping:** vegetation biophysical and biochemical properties;
5. **Methods of classifying:** vegetation types, species types, crop types;
6. **Methods of Separating\discriminating: vegetation types and their biophysical and biochemical quantities;**
7. **Concluding thoughts:** major gains in using hyperspectral data.



Importance of
Hyperspectral Sensors (Imaging Spectrometry) in
Study of Vegetation



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Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Importance for Hyperspectral Sensors (Imaging Spectroscopy) in Study of Vegetation

Some of the Major Needs of Hyperspectral Data in the Study of Vegetation are to:

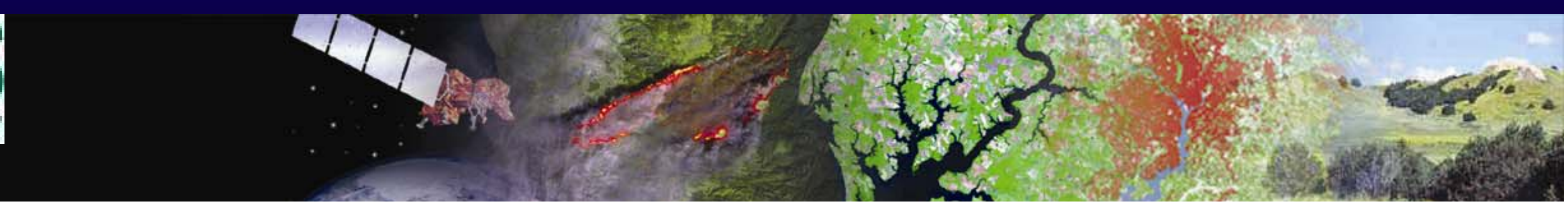
A. Study plant matter: Between 1995 and 2005, the global demand for plant matter increased by approximately five percent. That is, in 1995, we consumed 20.3 percent of the plant material that Planet Earth produced (the photosynthetic capacity of the land) but by 2005, that number increased to 25.6 percent both because of increased consumption of plant material per person and an increase in population. (Imhoff et al.);

B. Overcome limitations of broadband data in studying vegetation biophysical and biochemical parameters, species composition, land use classification etc. is well known;

C. Establish increased understanding, modeling, and mapping of our croplands and their water use in order to ensure global food security;

D. Develop targeted applications (e.g., moisture sensitive band, PRI, crop stress) require us to pick a narrowband (5 nm wide) from specific wavelength.

E. Reduce uncertainties in NPP\LUE etc. that will lead to improved understanding of "missing carbon" in global carbon budgets;



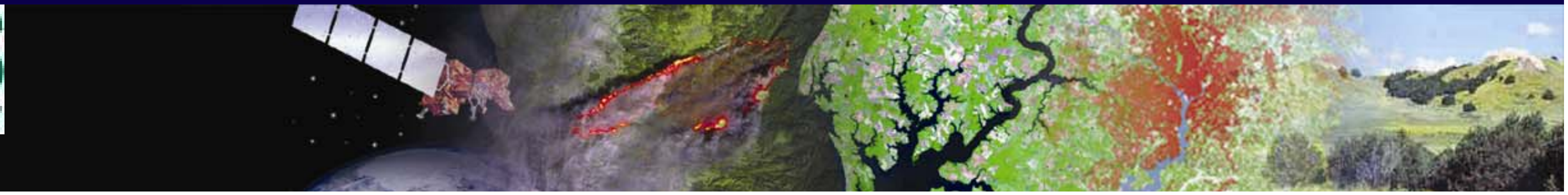
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Importance of Hyperspectral Sensors (Imaging Spectroscopy) in Study of Vegetation

More specifically…………..hyperspectral Remote Sensing, originally used for detecting and mapping minerals, is increasingly needed for to characterize, model, classify, and map agricultural crops and natural vegetation, specifically in study of:

(a)Species composition (e.g., *chromolenea odorata vs. imperata cylindrica*);
(b)Vegetation or crop type (e.g., soybeans vs. corn);
(c)Biophysical properties (e.g., LAI, biomass, yield, density);
(d)Biochemical properties (e.g, Anthrocyanins, Carotenoids, Chlorophyll);
(e)Disease and stress (e.g., insect infestation, drought),
(f)Nutrients (e.g., Nitrogen),
(g)Moisture (e.g., leaf moisture),
(h)Light use efficiency,
(i)Net primary productivity and so on.

……….in order to increase accuracies and reduce uncertainties in these parameters……..



Definition of
Hyperspectral Sensors (Imaging Spectrometry) in
Study of Vegetation

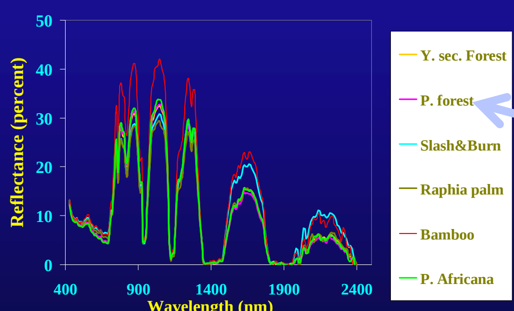
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

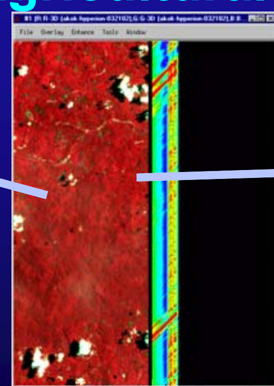
Definition of Hyperspectral Data

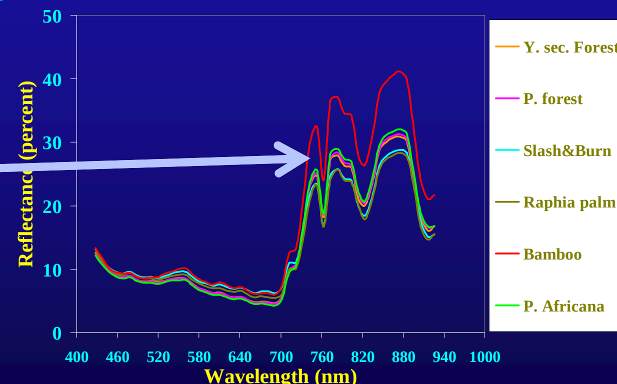
A. consists of hundreds or thousands of narrow-wavebands (as narrow as 1; but generally less than 5 nm) along the electromagnetic spectrum;

B. it is important to have narrowbands that are contiguous for strict definition of hyperspectral data; and not so much the number of bands alone (Qi et al. in Chapter 3, Goetz and Shippert).

…………Hyperspectral Data is fast emerging to provide practical solutions in characterizing, quantifying, modeling, and mapping natural vegetation and agricultural crops.







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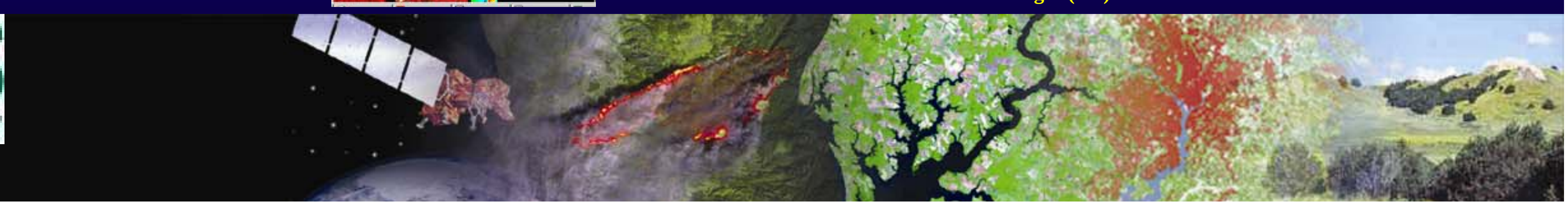
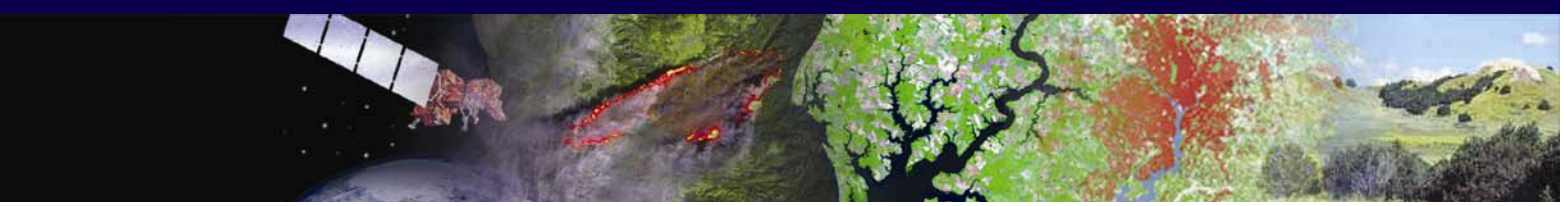


Hyperspectral Sensors (Imaging Spectroscopy)

Ground-based, Truck-Mounted, Airborne, Spaceborne



Advanced Hyperspectral Remote Sensing of Terrestrial Environment
Ground-based, Truck-mounted, and Airborne Sensors

A. Ground-based and truck-mounted measurements are made using spectroradiometers or spectrometers that typically gather data approximately every nanometer between 400-2500 nm;

B. Airborne hyperspectral sensors (or imaging spectrometers) include AVIRIS, HYDICE, AISA, HyMAP, ARES, CASI 1500, and AisaEAGLET. These sensors gather data in tens or hundreds of narrow wavebands (< 5 nm bandwidth), typically over the 400-2500 nanometers. The spatial resolution of airborne hyperspectral images are generally in the meters range and can change depending on the flight characteristics and the sensor equipment used. Hyperspectral data gathered from airborne sensors, at low heights, reaches sub-meter spatial resolutions.

Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Ground-based Hyperspectral Sensors: Two Spectroradiometers

FieldSpec® UV/VNIR (350-1100 nm)

FieldSpec® FR (350-2500 nm)

Spectroradiometer:

- unit consists of a main spectrometer, a personal computer, fiber optic cable, a pistol grip, and different field of view (FOV) cones.
- Inside the spectrometer instrument, light is projected from the fiber optics onto a holographic diffraction grating where wavelength components are separated and reflected for independent collection by the detector(s) (FieldSpec, 1997).

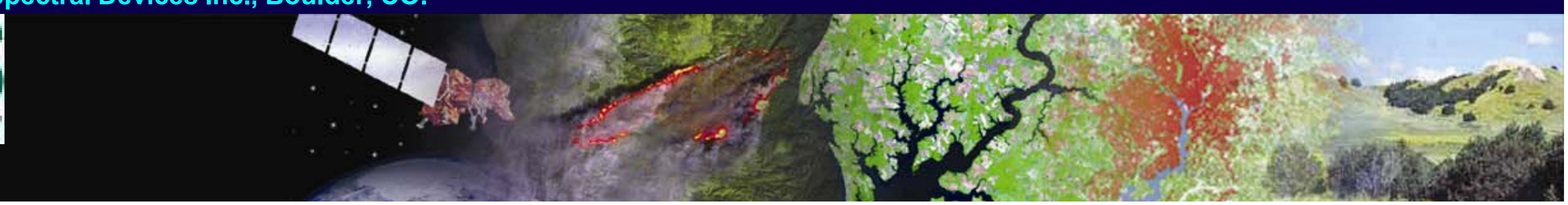
Target Reflectance:

- Energy reflected off the target to energy incident on the target (measured using a $BASO_4$ white reference).

Canopy-level Measurements:

- Acquired at a height of approximately 1.20 m above the ground, with a 38 cm diameter footprint on the ground, resulting in an area of 1134 cm^2 observed on ground.

Manufacturer: Analytical Spectral Devices Inc., Boulder, CO.



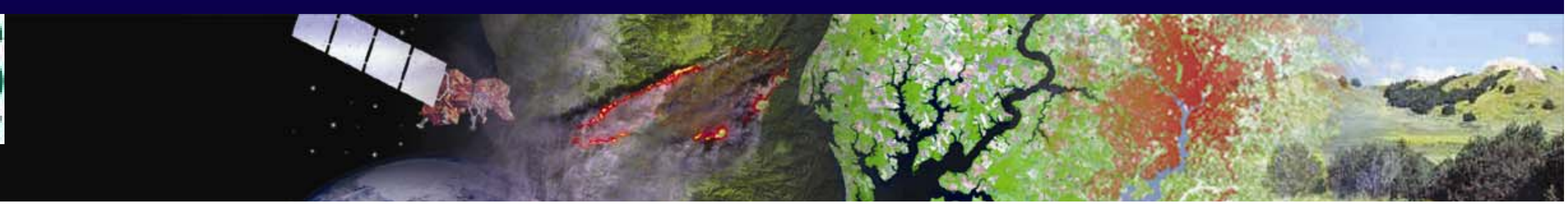
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Truck-mounted Hyperspectral sensors

The advantage of airborne, ground-based, and truck-mounted sensors are that they enable relatively cloud free acquisitions that can be acquired on demand anywhere; over the years they have also allowed careful study of spectra in controlled environments to advance the genre.

(a) (b) (c)

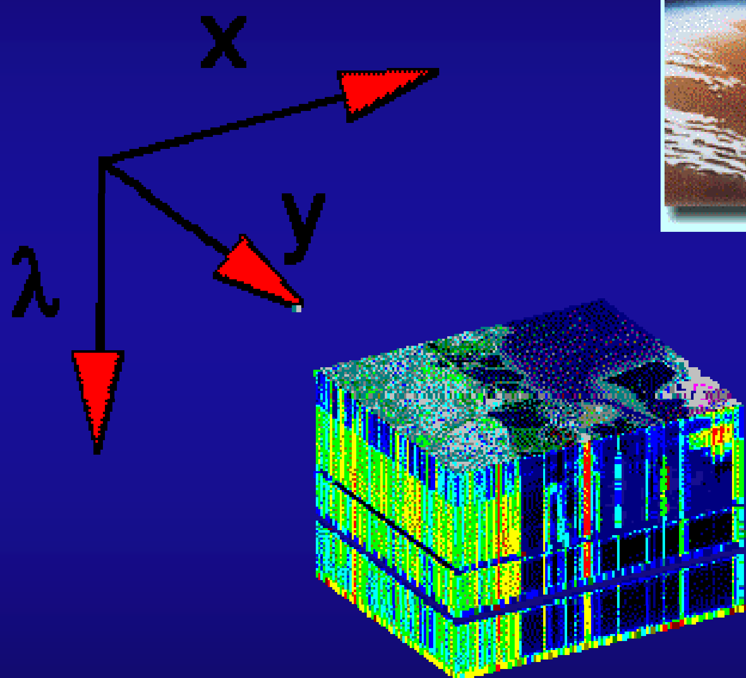
Truck-mounted Hyperspectral Data Acquisition example

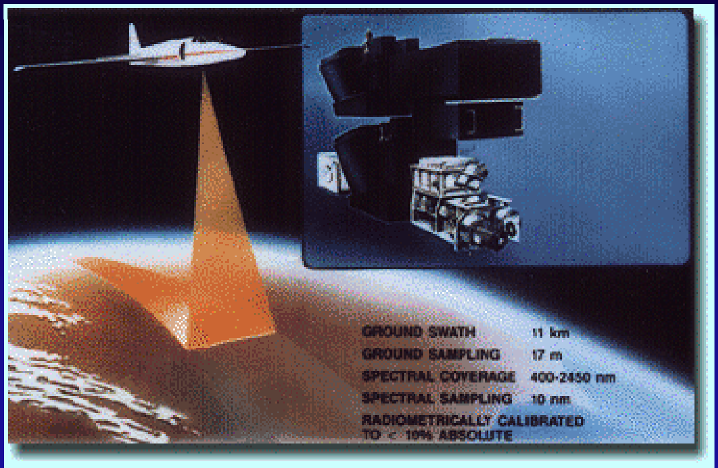


Advanced Hyperspectral Remote Sensing of Terrestrial Environment

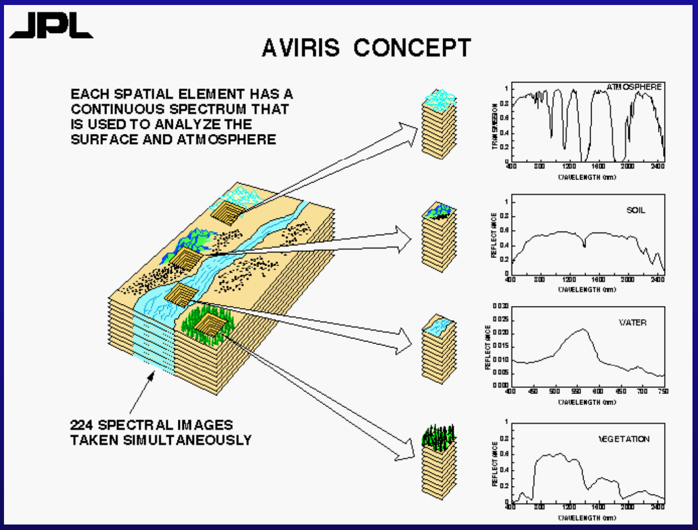
Airborne Sensors or Imaging Spectroscopy

Hyperspectral Data from AVIRIS

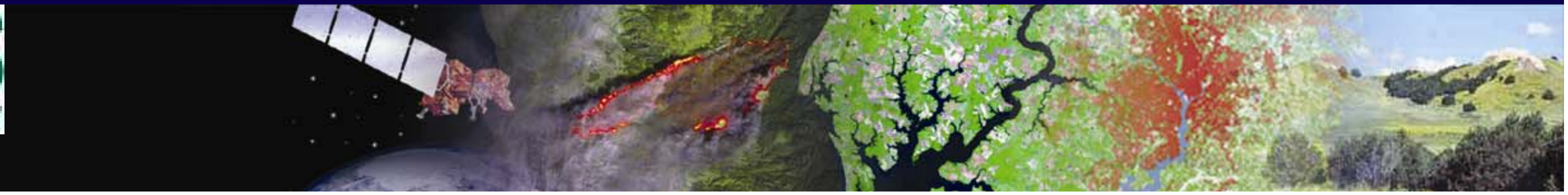




AVIRIS Gathers data in 224 bands in 400-2500 nm



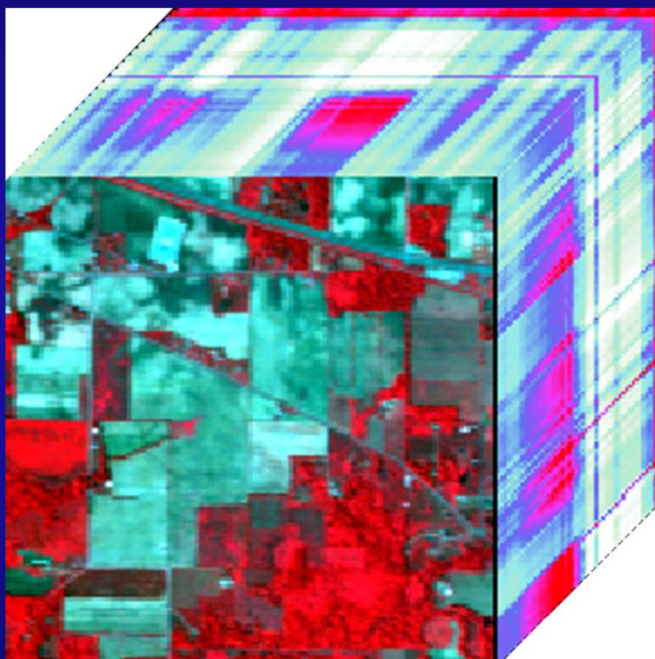
AVIRIS (Airborne Visible InfraRed Imaging Spectrometer)
Source: JPL (Jet Propulsion Laboratory; California Institute of Technology).



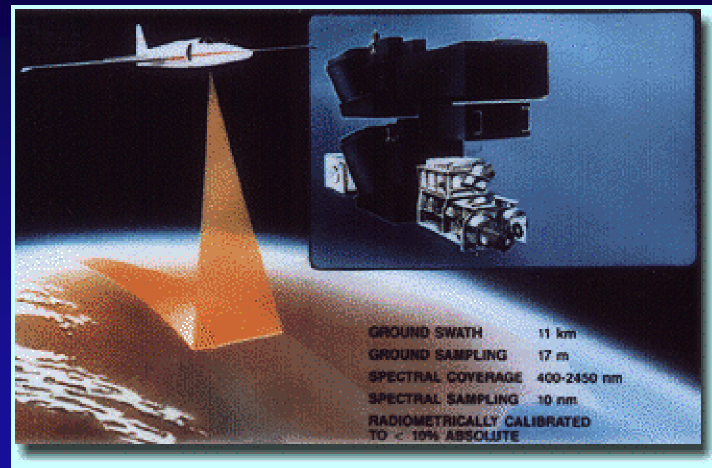
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Airborne Sensors or Imaging Spectroscopy

Hyperspectral Data Cube



Hyperspectral Data Cube (Source: LARS, Purdue University)



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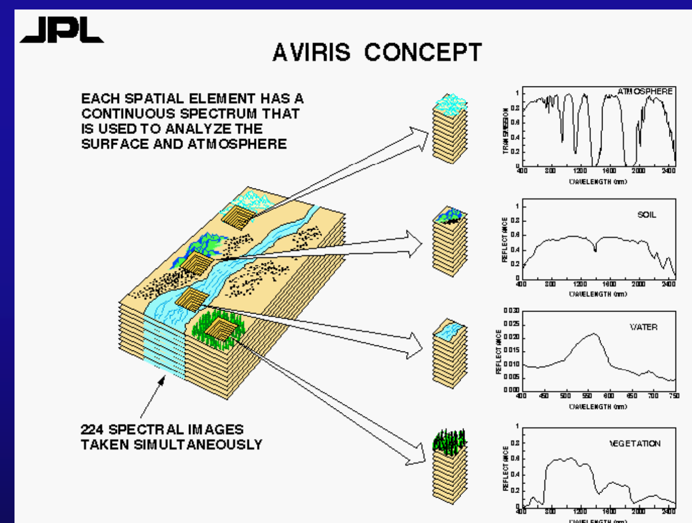

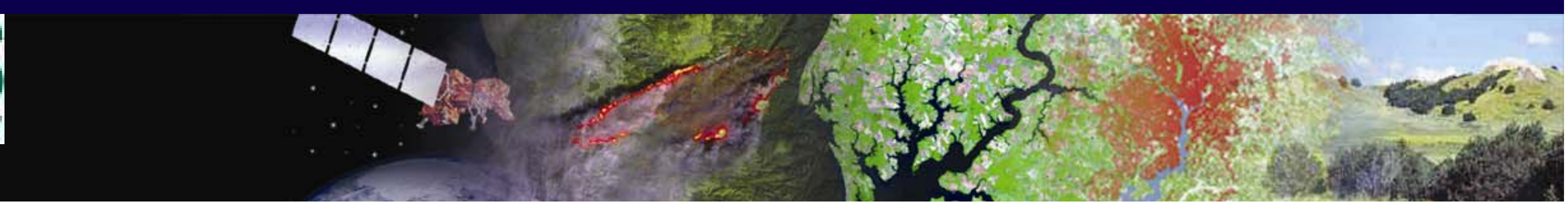

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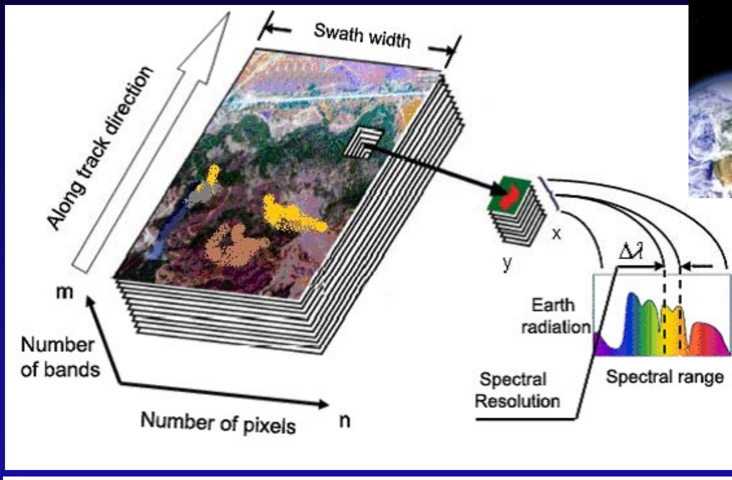
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Spaceborne Hyperspectral Sensors, their Characteristics, and Data Acquisition Concept



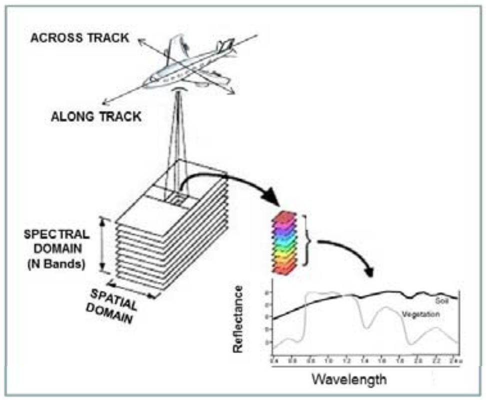


Fig 24

Instrument (Satellite)	Altitude, km	Pixel Size, m	Number Bands	Spectral Range, nm	Spectral Resolution, nm	IFOV, µrad	Swath, km
HSI (SIMSA)	523	25	220	430-2400	20	47.8	7.7
FTHSI (MightySatII)	565	30	256	450-1050	10-50	50	13
Hyperion (EO-1)	705	30	220	400-2500	10	42.5	7.5
CHRIS (PROBA)	580	25	19	400-1050	1.25-11.0	43.1	17.5
COIS (NEMO)	605	30	210	400-2500	10	49.5	30
ARIES-1 (ARIES-1)	500	30	32 32 32	400–1100 2000-2500 1000-2000	22 16 31	60	15
UKON-B	400	20	256	400-800	4-8	50	15
Warfighter-1 (OrbView-4)	470	8	200 80	450-2500 3000-5000	11	20	5
EnMAP	675	30	92 108	420-1030 950-2450	5-10 10-20	30	30
HypSEO (MITA)	620	20	~210	400-2500	10	40	20
MSMI (SUNSAT)	660	15	~200	400-2350	10	22	15
PRISMA	695	30	250	400-2500	<10	40	30
ARTEMIS (TacSat-3)	425	4	400	400-2500	5	70	~10
HyspIRI	~700	60	>200	380-2500	10	80	145
SUPERSPEC (MYRIADE)	720	20	8	430-910	20	30	120
VENµS	720	5.3	12	415-910	16-40	8	27.5
Global Imager (ADEOS-2)	802	250-1000	36	380-1195	10-1000	310-1250	1600
WFIS (like MODIS)	705	1400	630	400-1000	1-5	2000	2400

Note: see chapter 2, 24

Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Spaceborne Hyperspectral Imaging Sensors: Some Characteristics

Instrument (Satellite)	Altitude, km	Pixel Size, m	Number Bands	Spectral Range, nm	Spectral Resolution, nm	IFOV, µrad	Swath, km
HSI (SIMSA)	523	25	220	430-2400	20	47.8	7.7
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WFIS (like MODIS)	705	1400	630	400-1000	1-5	2000	2400

Existing hyperspectral spaceborne missions:

1. Hyperion (USA's NASA): 242 bands each 10 nm 400-2500 nm
2. PROBA (Europe's ESA;'s): 19 bands, 1.25 to 11 nm, 400-2500 nm

There are some twenty spaceborne hyperspectral sensors

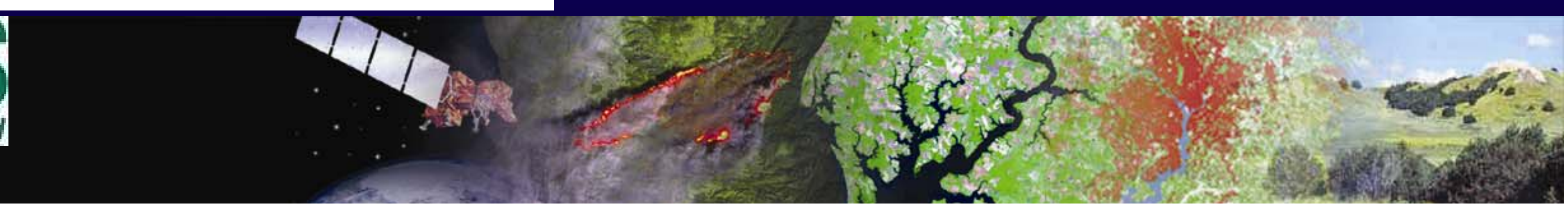
The advantages of spaceborne systems are their capability to acquire data: (a) continuously, (b) consistently, and (c) over the entire globe. A number of system design challenges of hyperspectral data are discussed in Chapter 3 by Qi et al. Challenges include cloud cover and large data volumes.

The 4 near future hyperspectral spaceborne missions:

1. PRISMA (Italy's ASI's),
2. EnMAP (Germany's DLR's), and
3. HISUI (Japanese JAXA);
4. HyspIRI (USA's NASA).

will all provide 30-60 m spatial resolution hyperspectral images with a 30 km swath width……HyspIRI: >200 bands in 380 to 2500 nm, 60 m spatial resolution, 8 TIR bands, 145 km swath, 19 days global coverage.

The multi-angular hyperspectral observation capability may be one of next important steps in the field of hyperspectral remote sensing.



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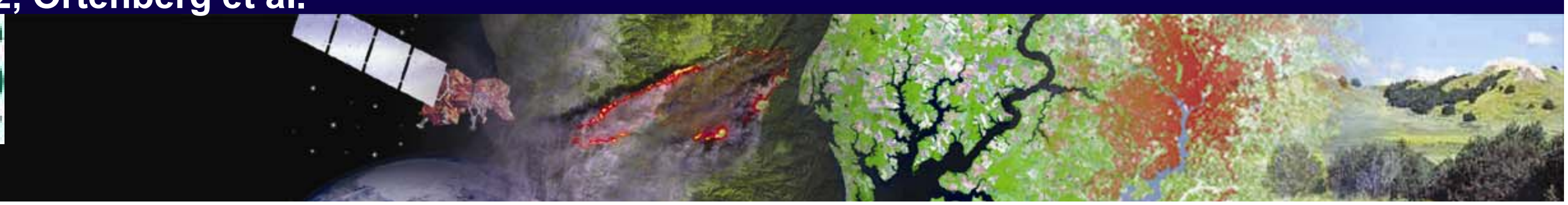
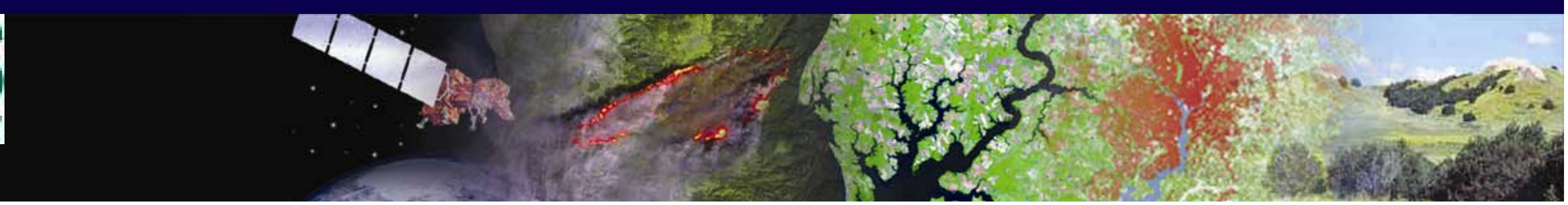
Commercial Applications of Hyperspectral Data: Few Examples

1. Drug enforcement-like vehicle-mounted monitoring of illicit substance cultivation;
2. Marine biosphere monitoring in a hand-held or vehicle-mounted underwater configuration;
3. Forensic science and crime scene investigation and detection of counterfeit notes;
4. Environmental and toxicological monitoring of airborne or waterborne pollutants;
5. Mining and petroleum exploration;
6. Mapping of forest fires;
7. Medical applications for retinal imaging, colonoscopy, and skin cancer detection.

Note: see chapter 2, Ortenberg et al.

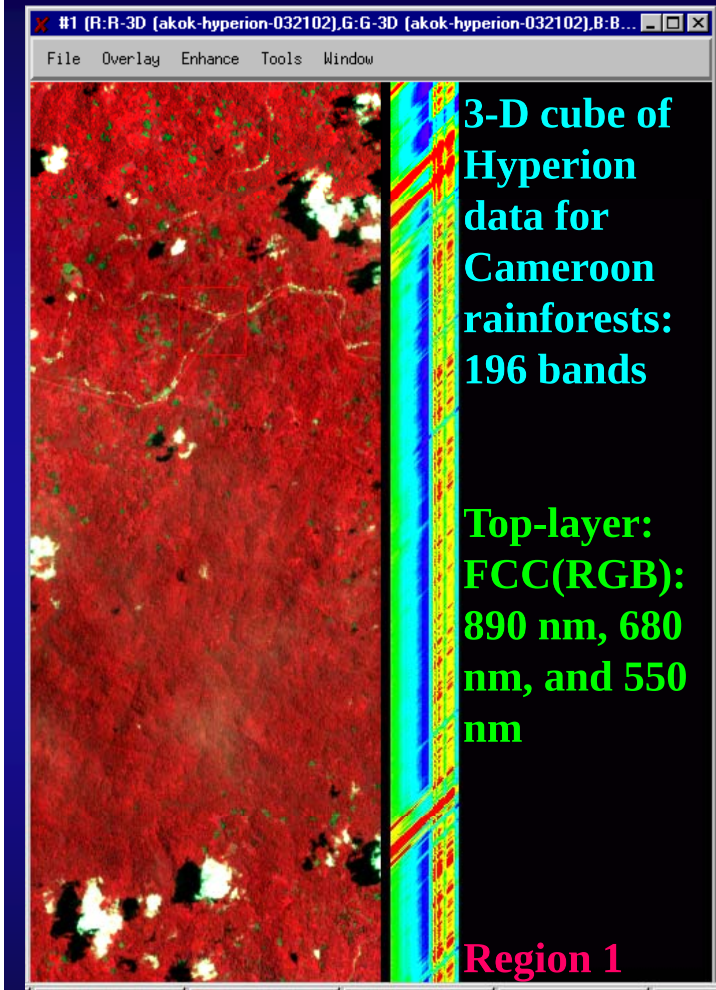


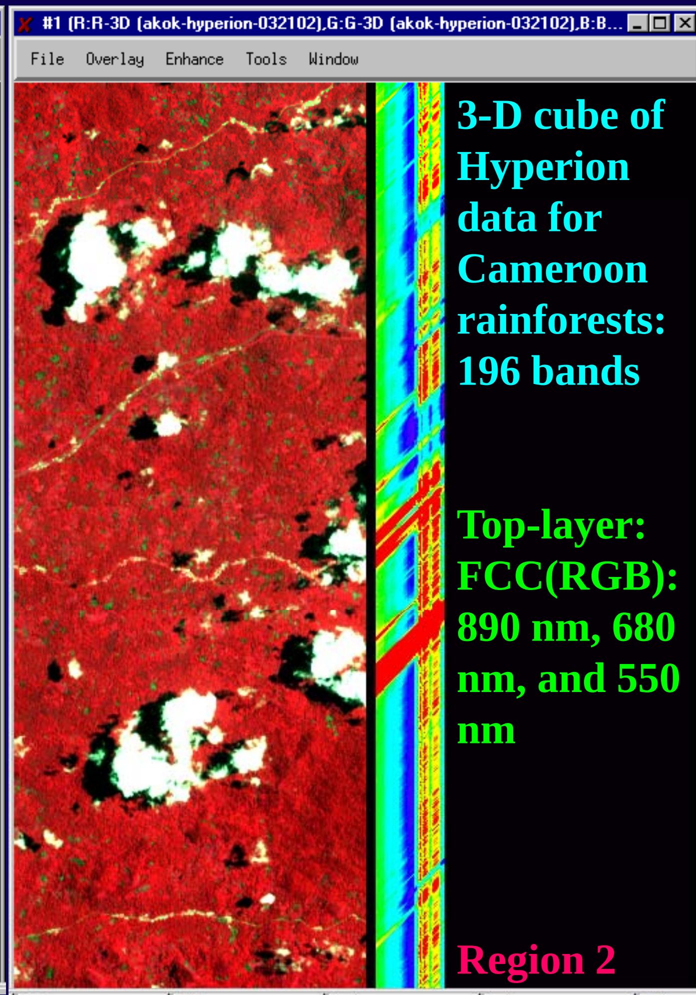
Hyperspectral Data Characteristics
Ground-based, Truck-Mounted, Airborne, Spaceborne

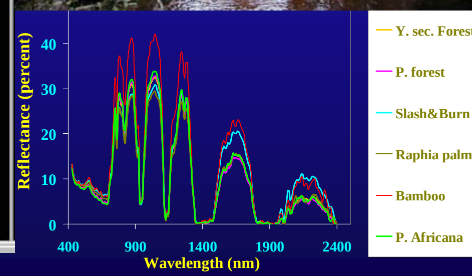


Hyperion Data from EO-1 (e.g., in Rainforests of Cameroon)

Hyperspectral Data Cube Providing Near-continuous data of 100's of Wavebands







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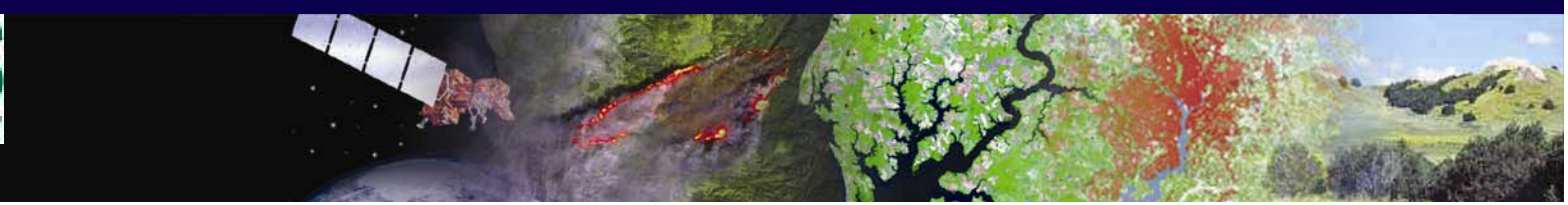
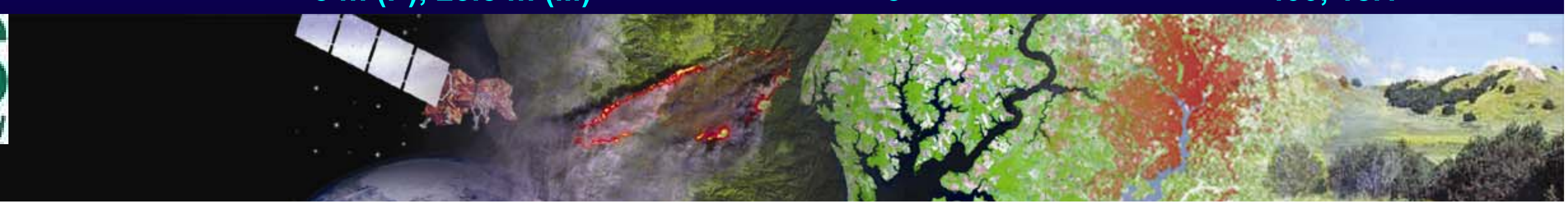


Comparison of Hyperspectral Data with Data from Other Advanced Sensors

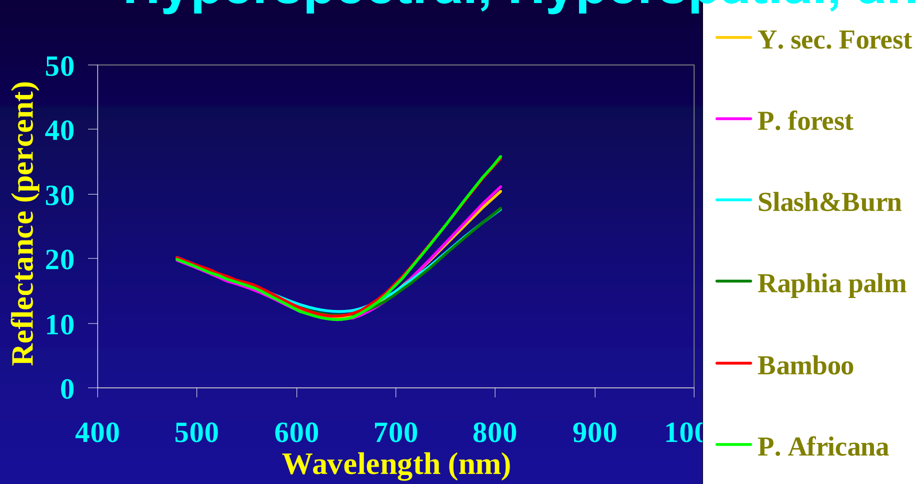
Hyperspectral, Hyperspatial, and Advanced Multi-spectral Data

Satellite/Sensor or pixels	spatial resolution (meters)	spectral bands (#)	data points per hectare
Earth Observing-1			
Hyperion	30	196 (400-2500 nm)	11.1
ALI	10 m (P), 30 m (M)	1, 9	100, 11.1
IKONOS 2	1 m (P), 4 m (M)	4	10000, 625
SpaceImaging			
QUICKBIRD	0.61 m (P), 2.44 m (M)	4	16393, 4098
Digital Globe			
Terra: Earth Observing System (EOS)			
ASTER	15 m, 30 m, 90 m (VNIR,SWIR,TIR)	4,6,5	44.4,11.1,1.26
MODIS	250-1000 m	36	0.16, 0.01
Landsat-7 ETM+	15 m (P), 30 m (M)	7	44.4,11.1
Landsat-4, 5 TM	30 m (M)	7	11.1
SPOT-1,2,3, 4,5 HRV	2.5 m. 5m, 10 m (P/M), 20 m (M)	4	
1600,400,100,25			
IRS-1C LISS	5 m (P), 23.5 m (M)	3	400, 18.1
IRS-1D LISS	5 m (P), 23.5 m (M)	3	400, 18.1

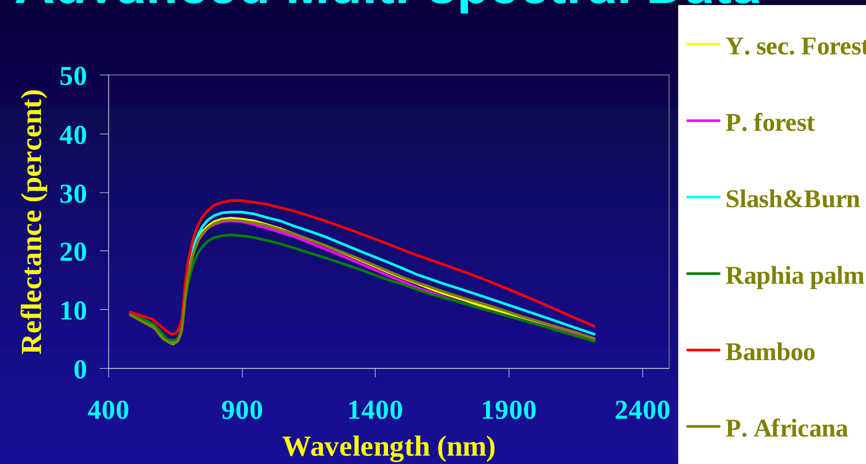


Comparison of Hyperspectral Data with Data from Other Advanced Sensors

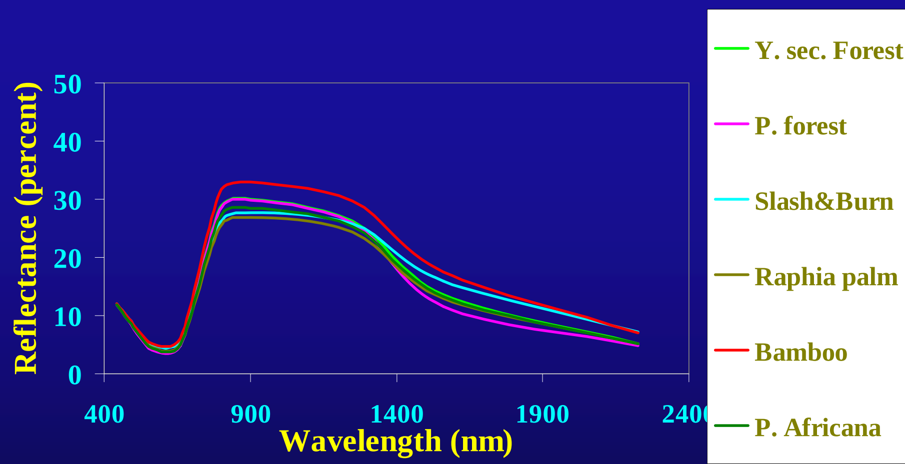
Hyperspectral, Hyperspatial, and Advanced Multi-spectral Data



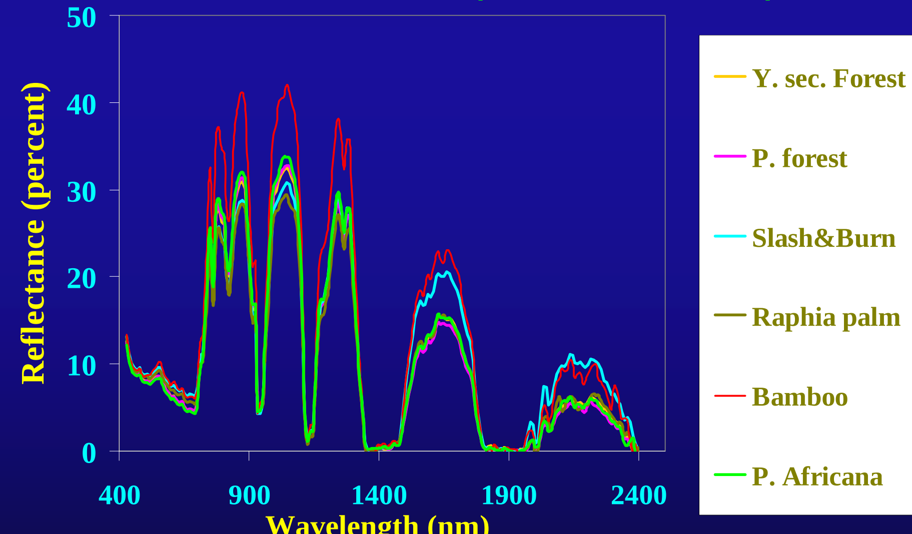
IKONOS: Feb. 5, 2002 (hyper-spatial)



ETM+: March 18, 2001 (multi-spectral)



ALI: Feb. 5, 2002 (multi-spectral)



Hyperion: March 21, 2002 (hyper-spectral)

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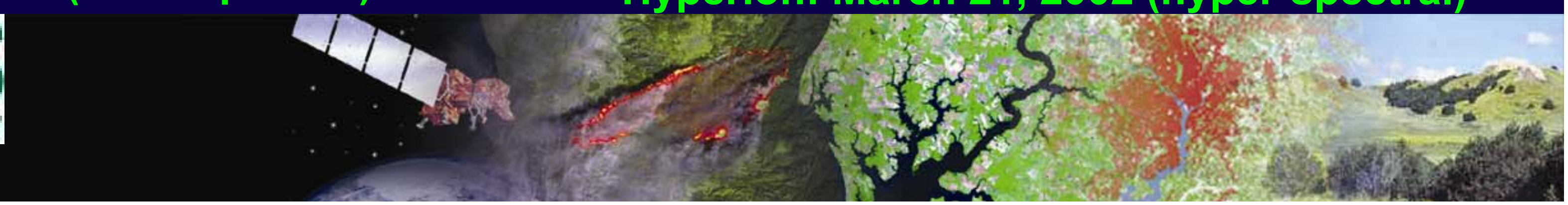

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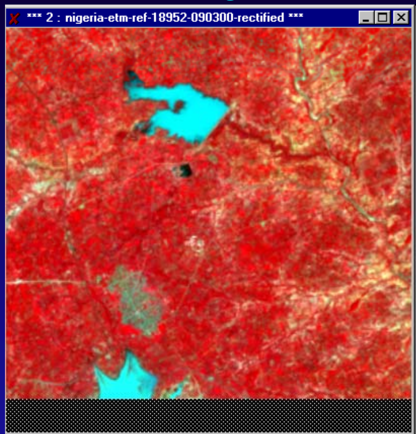
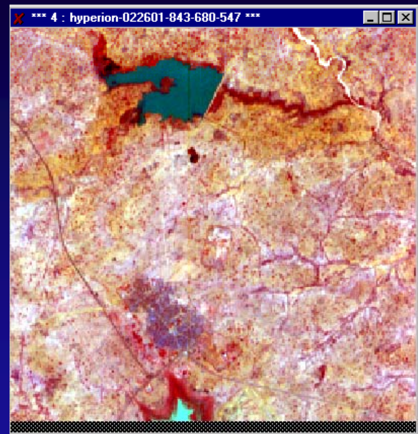
Hyperion Narrow-Band Data from EO-1 Vs. ETM+ Broad-band Data

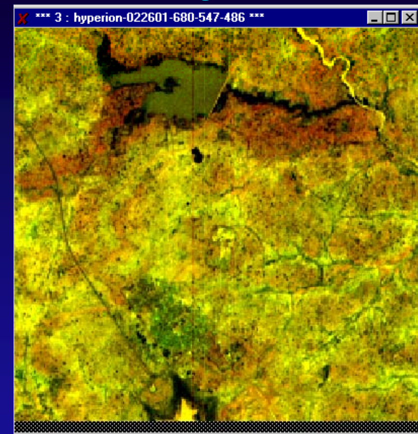
Hyperspectral Data Provides Numerous Ways of Looking at Data



ETM+:4,3,2

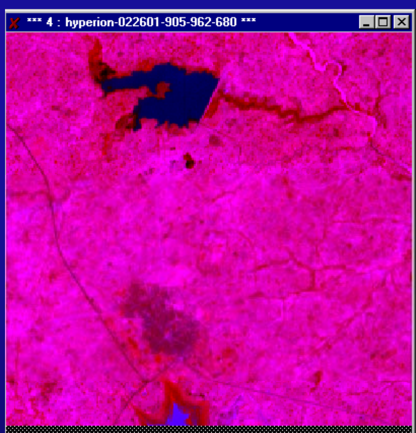


Hyperion:843, 680, 547

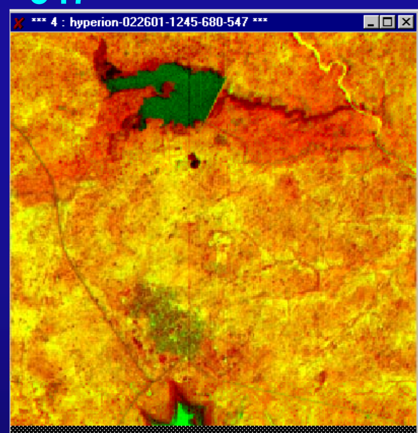


Hyperion: 680, 547, 486

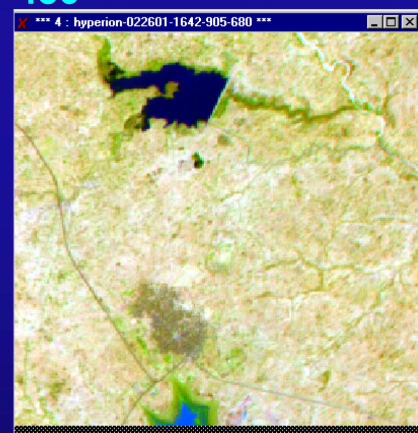
Hyperion:905, 680, 547



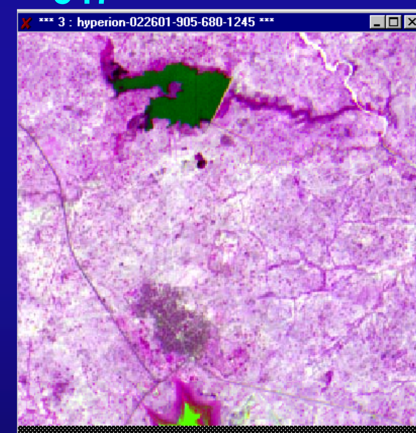
Hyperion:905, 962, 680



Hyperion:1245, 680, 547



Hyperion:1642, 905, 680



Hyperion:904,680,1245

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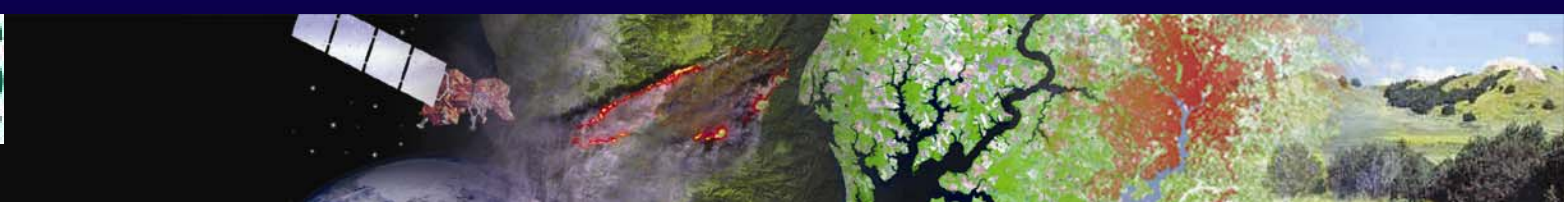


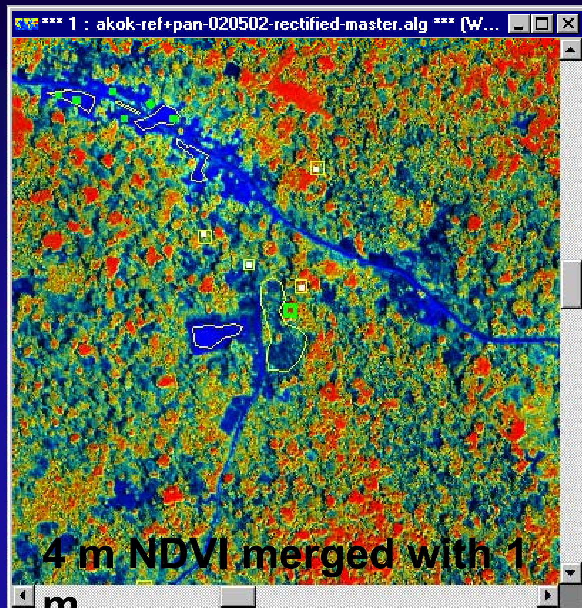
Comparison of Hyperspectral Data with Data from Other Advanced Sensors

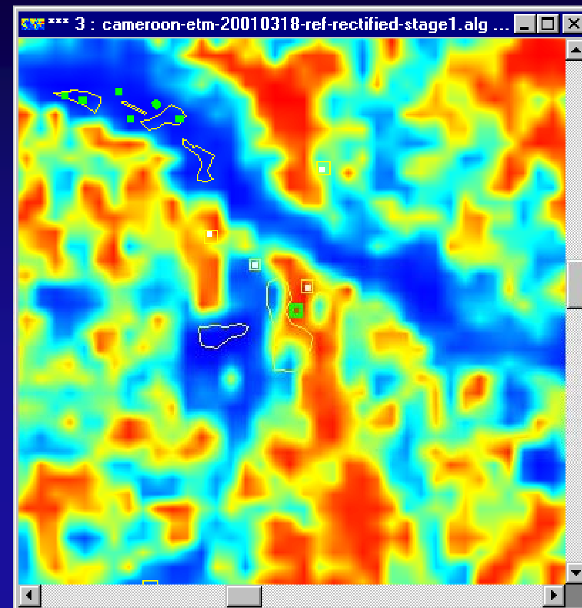
Hyperspectral, Hyperspatial, and Advanced Multi-spectral Data

IKONOS
NDVI:
0 to 0.56

Dynamic range: 0.56

(a) Broad-bands at NIR and red; (b) 11-bit data





ETM+ NDVI:
-0.17 to 0.45

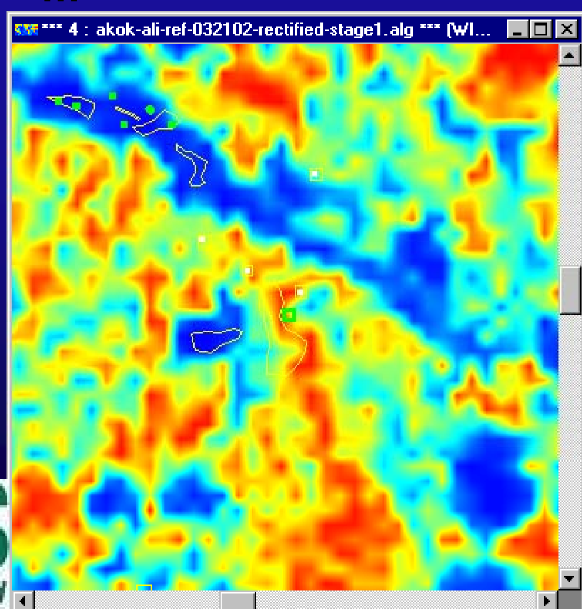
Dynamic range: 0.62

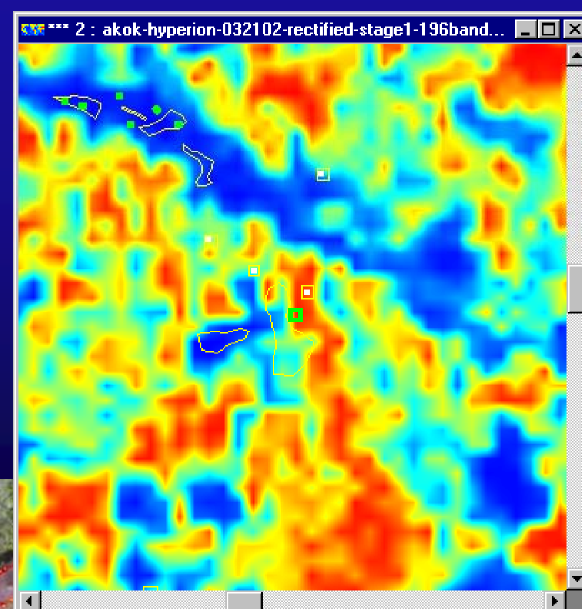
(a) Broad-bands at NIR and red; (b) 8-bit data

ALI NDVI:
-0.1 to 0.67

Dynamic range: 0.68

(a) Broad-bands at NIR and red; (b) 16-bit data





Hyperion
NDVI:
-0.2 to 0.62

Dynamic range: 0.82

(a) Narrow-bands at NIR and red; (b) 16-bit data

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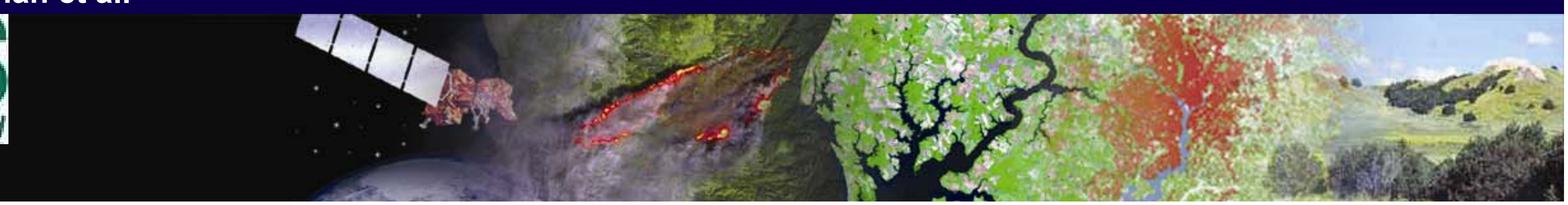
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Earth and Planetary Hyperspectral Remote Sensing Instruments

		Hyperspectral Instrument	Spectral Range (nm)	# of Channels	Spectral Bandpass	Spatial Resolution	Operational Dates
Earth							
	Airborne	AVIRIS[1]	380 - 2500	224	10 nm	4 - 20 m	1989 - present
		ProSpecTIR-VS[2]	400 - 2450	256	2.3 - 20 nm	1 - 10 m	~2000 - present
		HyMap[3]	400 - 2500	128	15 nm	2 - 10 m	~1997 - present
		CASI[4]	400 - 1000	288	2 - 12 nm	0.5 - 10 m	~1990 - present
		SFSI[5]	1230 - 2380	230	10 nm	0.5 - 10 m	1990 - present
	Spaceborne	EO-1 Hyperion[6]	400 - 2500	220	10 nm	30 m	2001 - present
Mercury		MESSENGER MASCS[7]	220 - 1450	768	0.2 - 0.5 nm	1 - 650 km	2004 - present
Moon		Chandrayaan-1 Moon Mineralogy Mapper[8]	400 - 2900	260	10 nm	70 - 140 m	2008 - 2009
Mars		Mars Express OMEGA[9]	350 - 5100	352	7 - 20 nm	300 m - 4.8 km	2003 - present
		Mars Reconnaissance Orbiter CRISM[10]	362 - 3920	545	6.55 nm	15.7 m - 200 m	2005 - present
Jupiter		Galileo NIMS[11]	700 - 5200	1 - 408	12.5 & 25 nm	50 - 500 km	1989 - 2003
Saturn		Cassini VIMS[12]	300 - 5100	352	7 & 14 nm	10 - 20 km	1997 - present

1 - Airborne Visible Infrared Imaging Spectrometer (http://aviris.jpl.nasa.gov)
2 - Spectral Technology and Innovative Research Corporation Hyperspectral Imaging Spectrometer (http://www.spectir.com/assets/Images/Capabilities/ProspecTIR%20specs.pdf)
3 - HyVista Corporation Hyperspectral Mapper, developed by Integrated Spectronics (http://www.hyvista.com/main.html and http://www.intspec.com)
4 - Compact Airborne Spectrographic Imager (http://www.geomatics-group.co.uk/GeoCMS/Products/CASI.aspx)
5 - SWIR Full Spectrum Imager (http://www.borstad.com/sfsi.html)
6 - Hyperion (http://eo1.gsfc.nasa.gov/Technology/Hyperion.html)
7 - Mercury Atmospheric and Surface Composition Spectrometer (http://www.messenger-education.org/instruments/mascs.htm)
8 - M^3 (http://moonmineralogymapper.jpl.nasa.gov/INSTRUMENT/)
9 - Observatoire pour la Minéralogie, l'Eau, les Glaces et l'Activité (http://sci.esa.int/science-e/www/object/index.cfm?fobjectid=34826&fbodylongid=1598)
10 - Compact Reconnaissance Imaging Spectrometer for Mars (http://crism.jhuapl.edu/)
11 - Near-Infrared Mapping Spectrometer (http://www2.jpl.nasa.gov/galileo/instruments/nims.html)
12 - Visual and Infrared Mapping Spectrometer (http://wwwvims.lpl.arizona.edu/)

See chapter 27, Vaughan et al.



Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Earth and Planetary Hyperspectral Remote Sensing Instruments

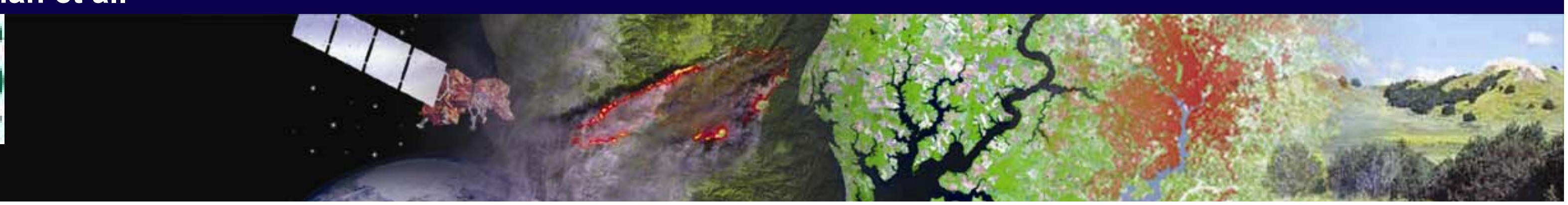
1. Methods used to acquire and calibrate planetary data sets share many similarities with those used for terrestrial observations of vegetated and rocky surfaces on Earth;

2. planetary bodies can range from those without atmospheres to those with atmospheres much thicker than on Earth;

3. There is a clear link between water and life in our: http://mepag.jpl.nasa.gov/reports/MEPAG_Goals_Document_2010_v17.pdf

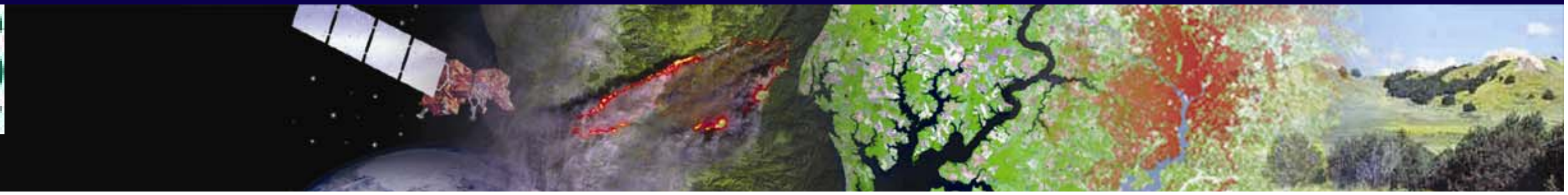
4. Geological and biological materials such that we will soon be able to characterize and preserve habitable environments both on and off the Earth.

See chapter 27, Vaughan et al.

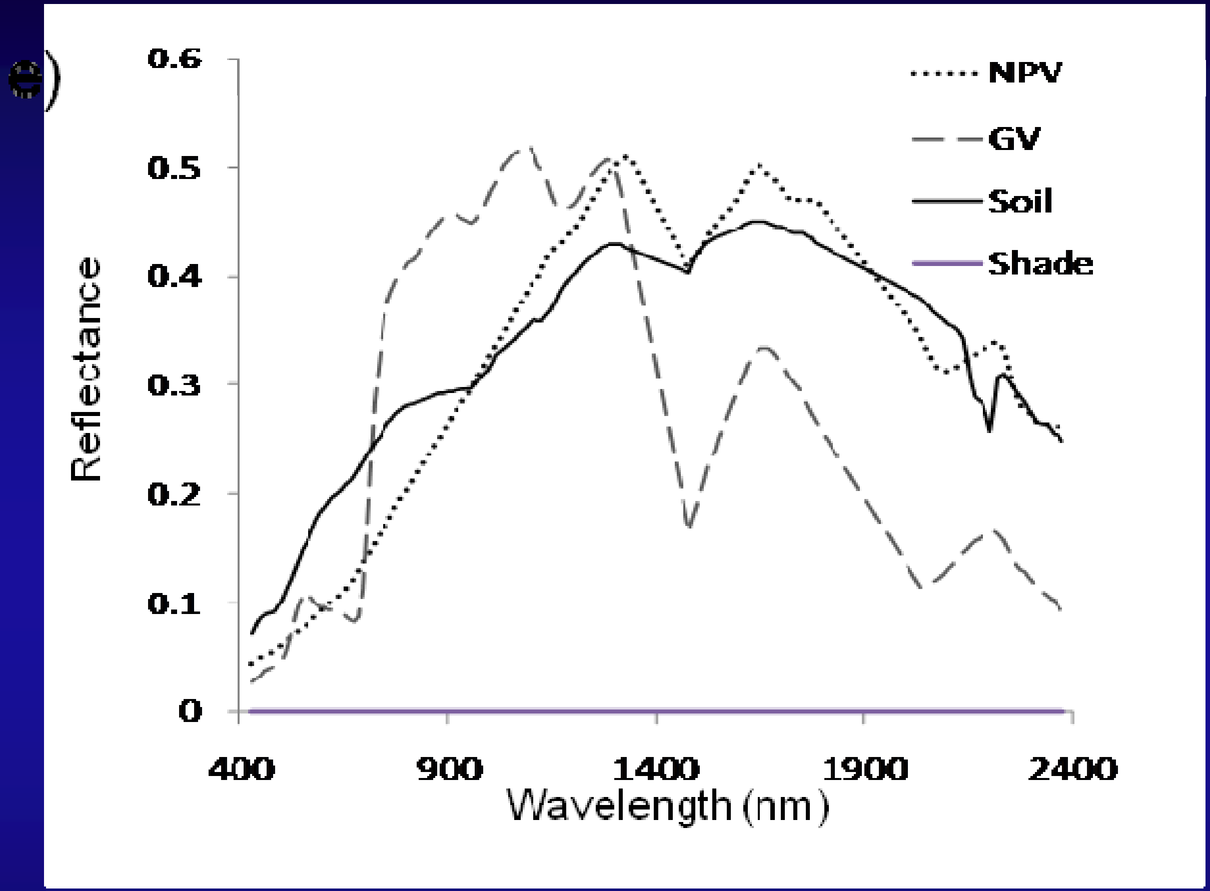


Hyperspectral Data Characteristics

Spectral Wavelengths and their Importance in Vegetation Studies

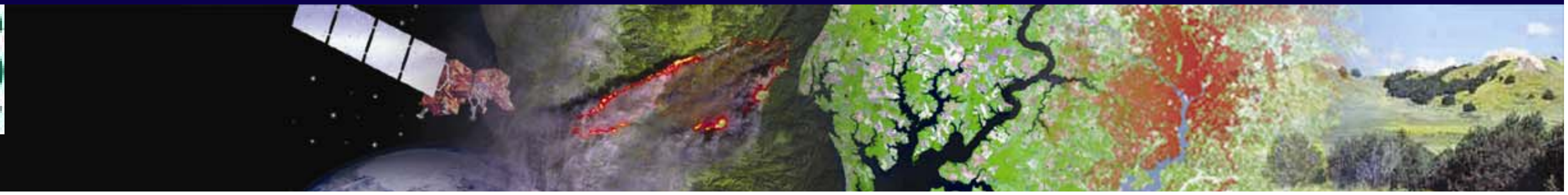


Advanced Hyperspectral Remote Sensing of Terrestrial Environment
Typical Hyperspectral Signatures of Certain Land Components



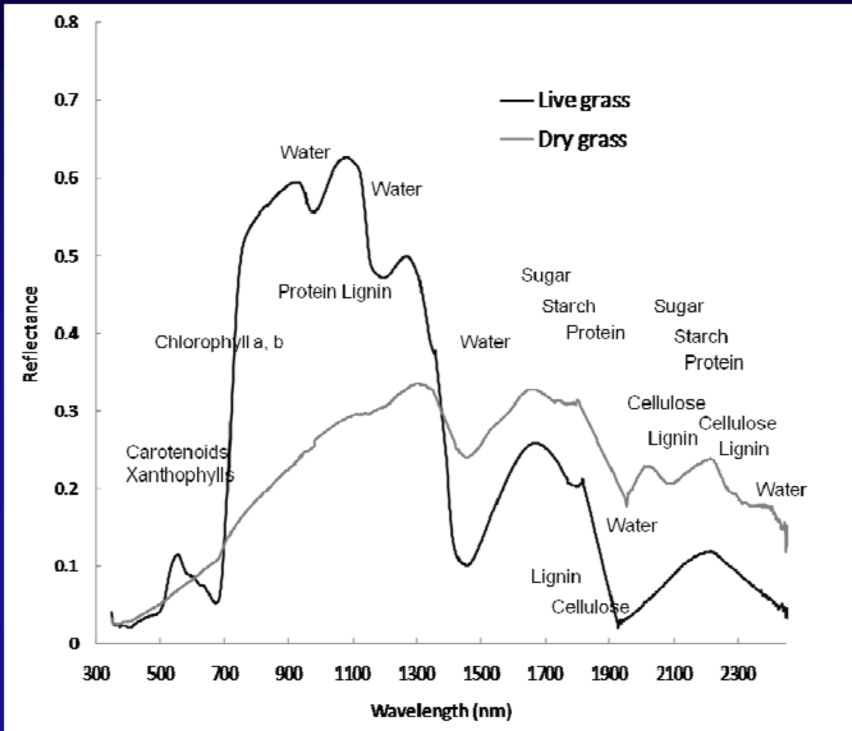
Fraction images of a pasture property in the Amazon derived from EO-1 Hyperion imagery. Four endmembers: (a) nonphotosynthetic vegetation (NPV); (b) green vegetation (GV); (c) Soil; and (d) Shade.

See chapter 9, Numata et al.



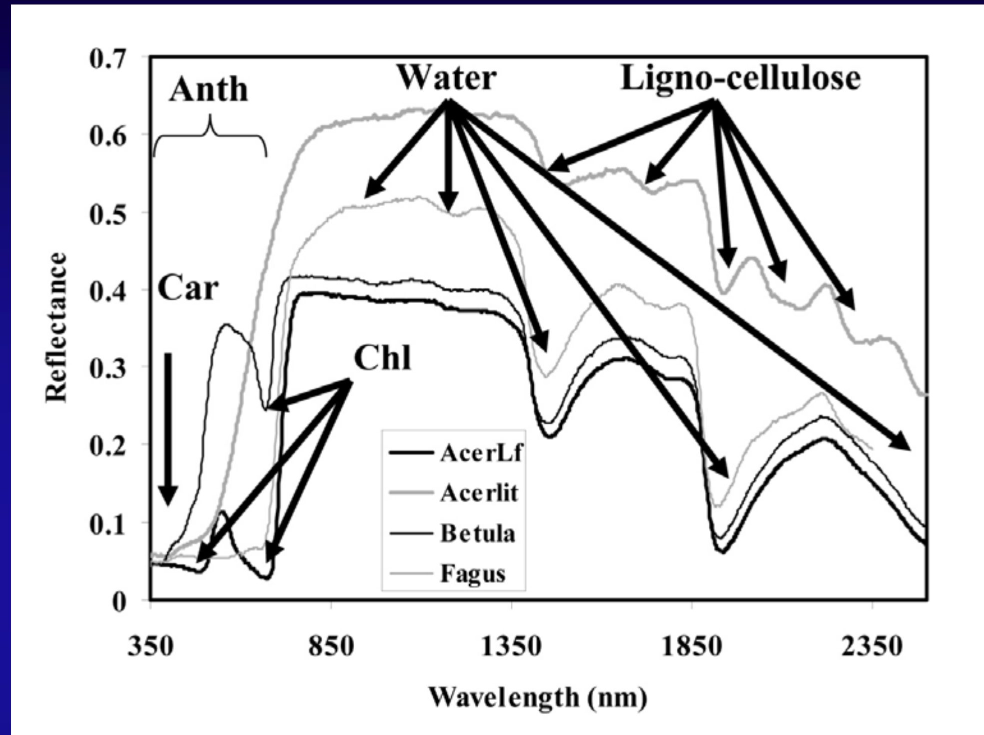
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Spectral Wavelengths and their Importance in the Study of Vegetation Biochemical properties



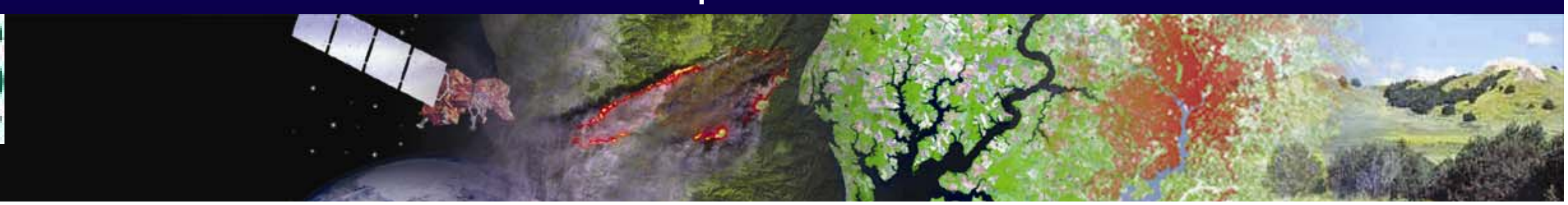
The reflectance spectra with characteristic absorption features associated with plant biochemical constitutents for live and dry grass (Adapted from Hill [13]).

See chapter 9



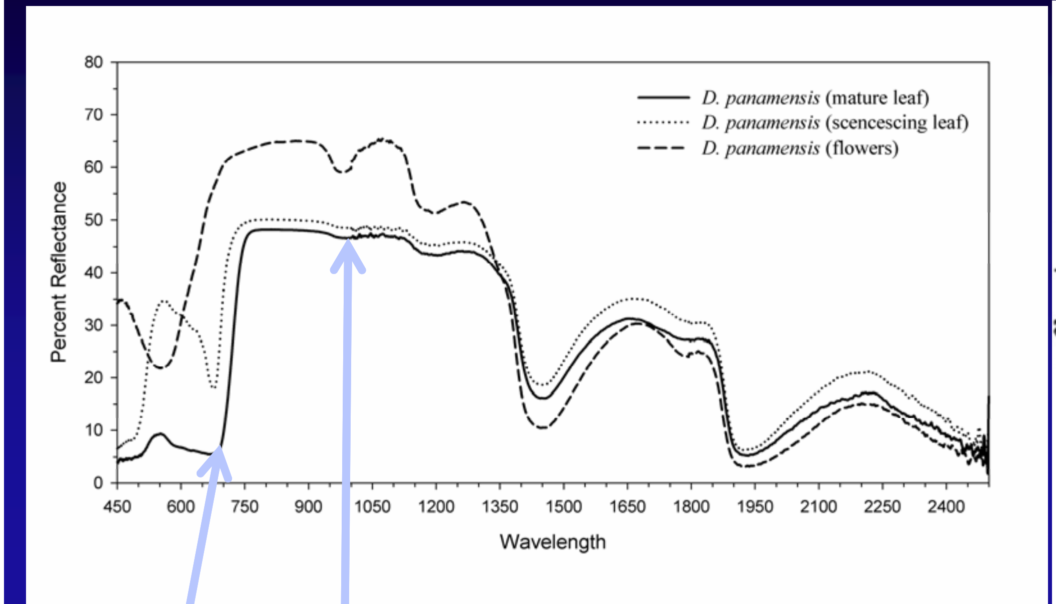
Reflectance spectra of leaves from a senesced birch (Betula), ornamental beech (Fagus) and healthy and fully senesced maple (AcerLf, Acerlit) illustrating Carotenoid (Car), Anthocyanin (Anth), Chlorophyll (Chl), Water and Ligno-cellulose absorptions.

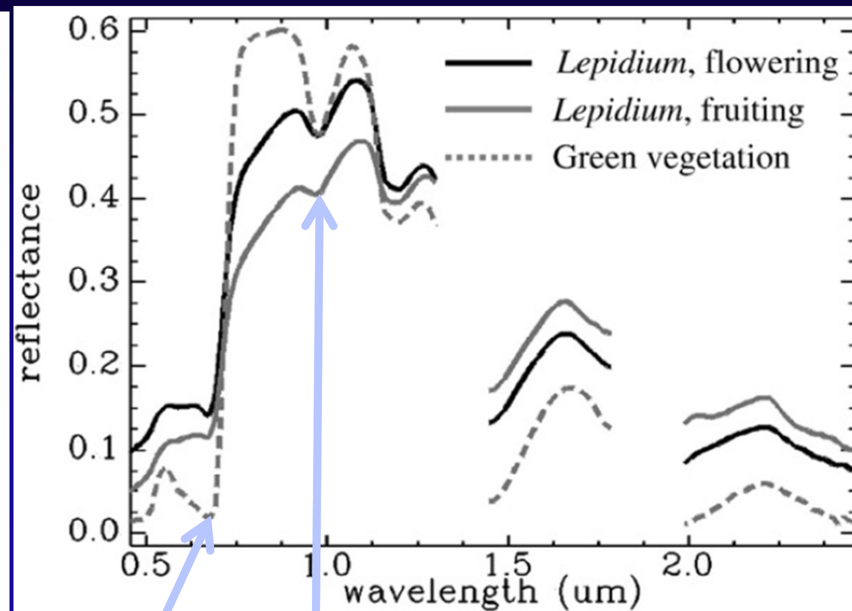
See chapter 14



Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Spectral Wavelengths and their Importance in the Study of Vegetation Biophysical Properties





Greater the biomass, LAI, moisture, greater is absorption @ 680 nm

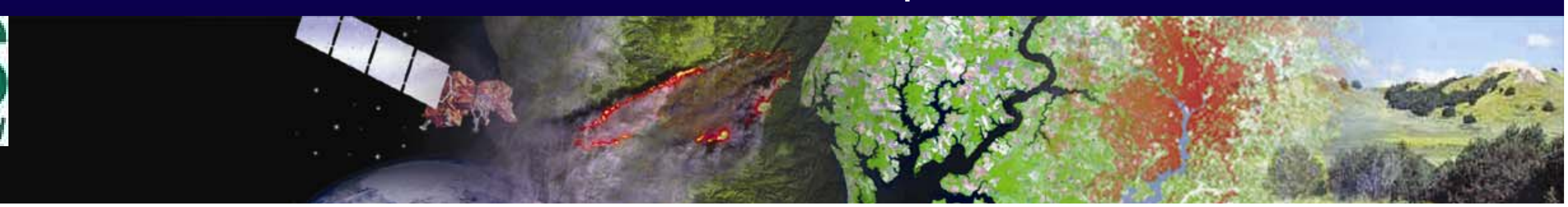
Greater the biomass, LAI, moisture, greater is absorption @ 970 nm

Greater the biomass, LAI, moisture, greater is absorption @ 680 nm

Greater the biomass, LAI, moisture, greater is absorption @ 970 nm

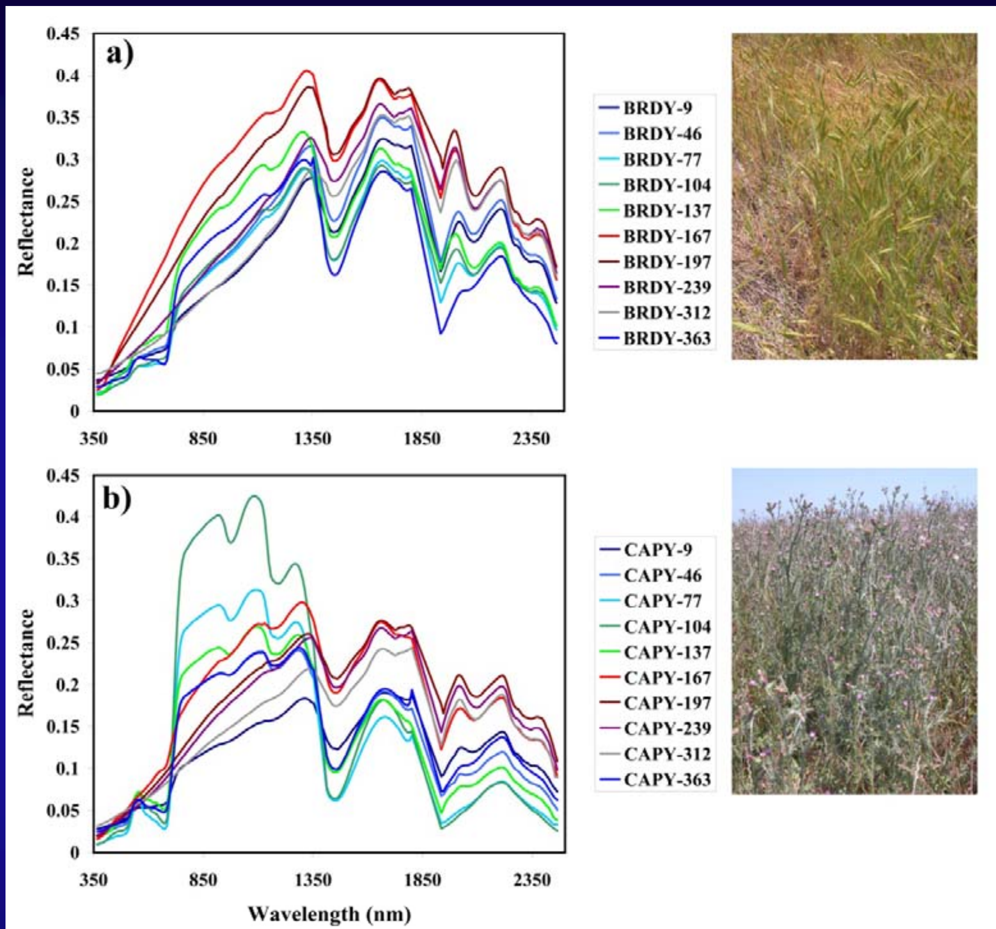
See chapter 18

See chapter 19

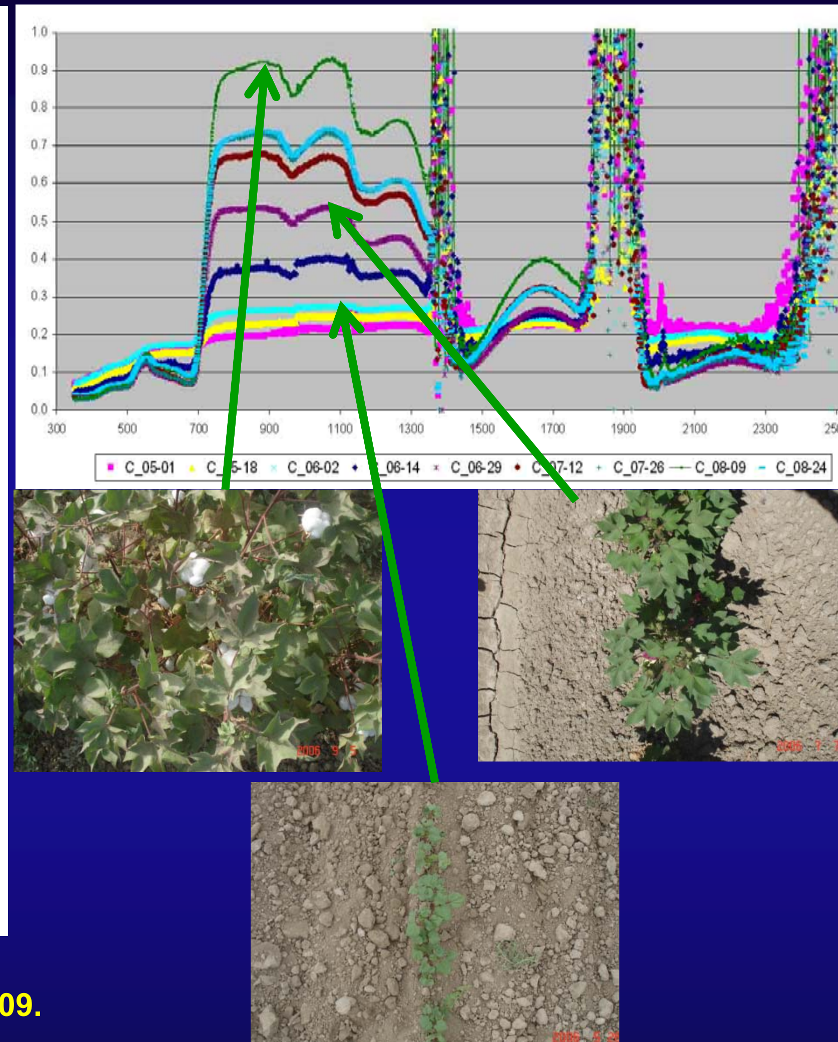


Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Spectral Wavelengths and their Importance in the Study of Vegetation over Time

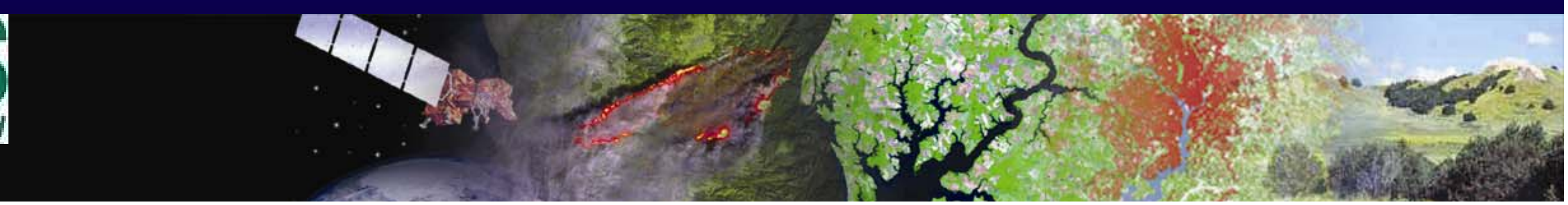


Natural Vegetation: Reflectance spectra of *Brachypodium distachyon* (BRDI) and *Carduus pychnocephalus* (CAPY) for 2009. The number to the right on the legend reports Julian day.



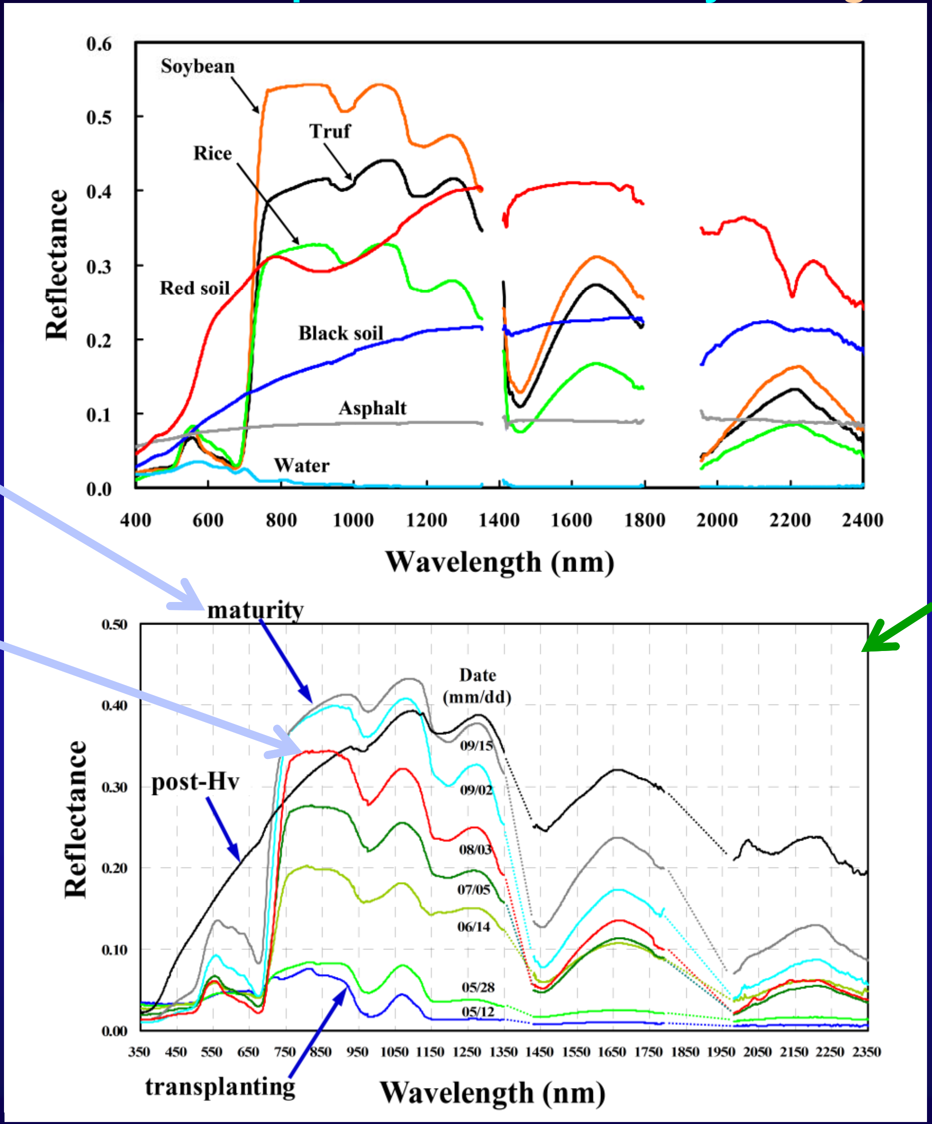
Agricultural Crop: e.g., Cotton over time

See chapter 14



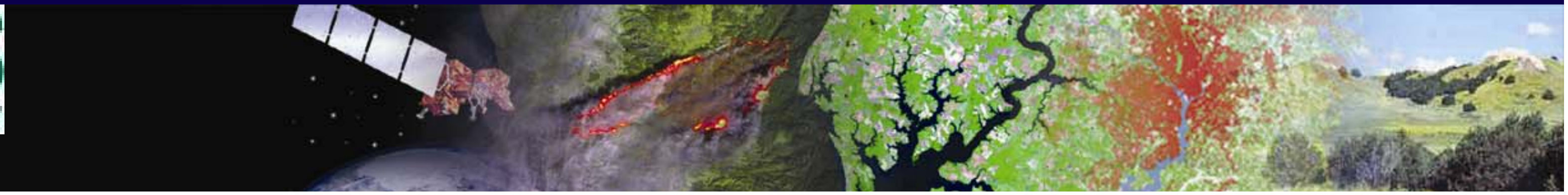
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Spectral Wavelengths and their Importance in the Study of Vegetation over Time



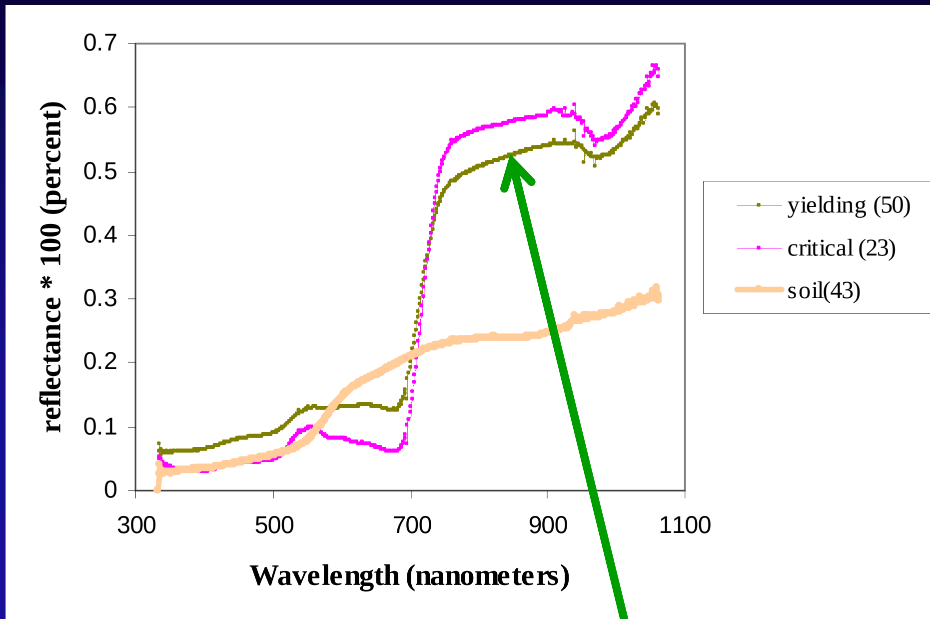
Typical reflectance spectra in agro-ecosystem surfaces (upper), and <u>seasonal changes</u> of spectra in a paddy rice field (lower).

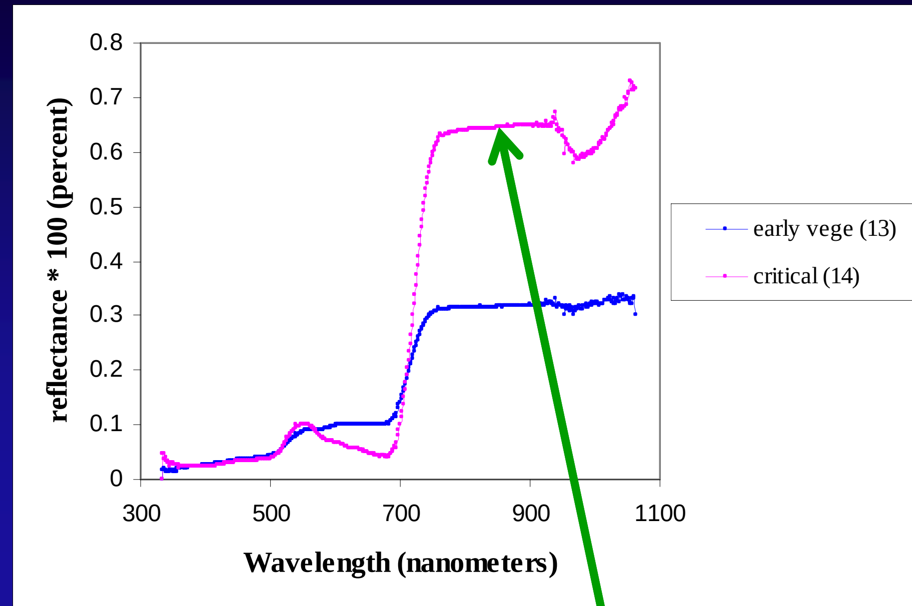
See chapter 3

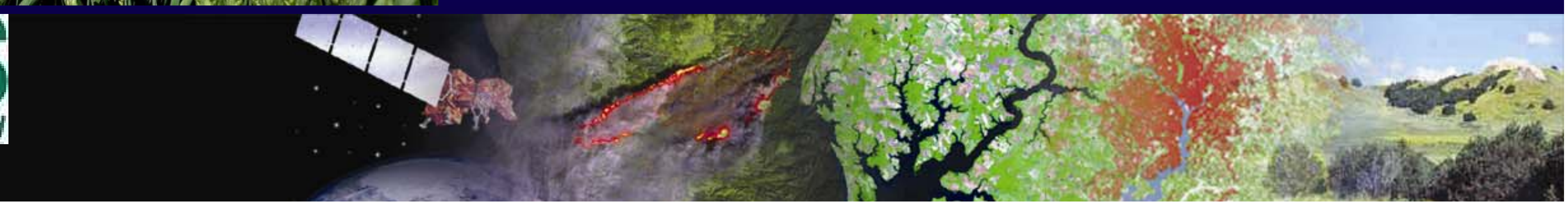


Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Spectral Wavelengths and their Importance in the Study of Vegetation Structure







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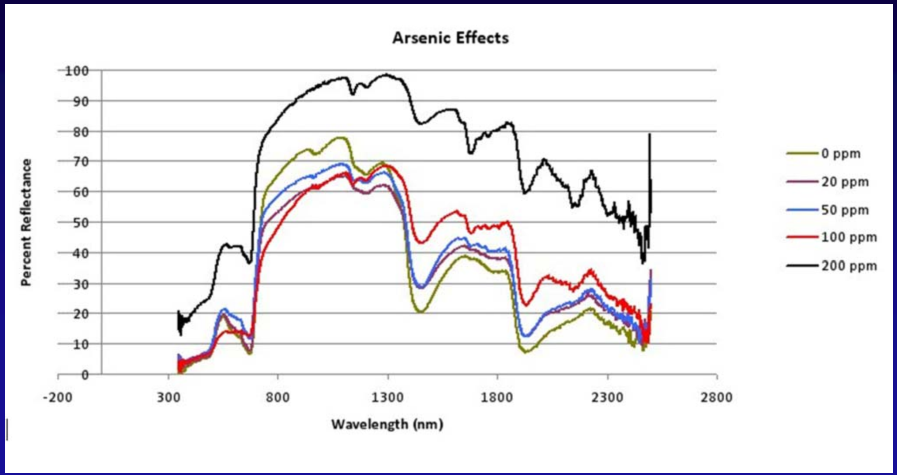
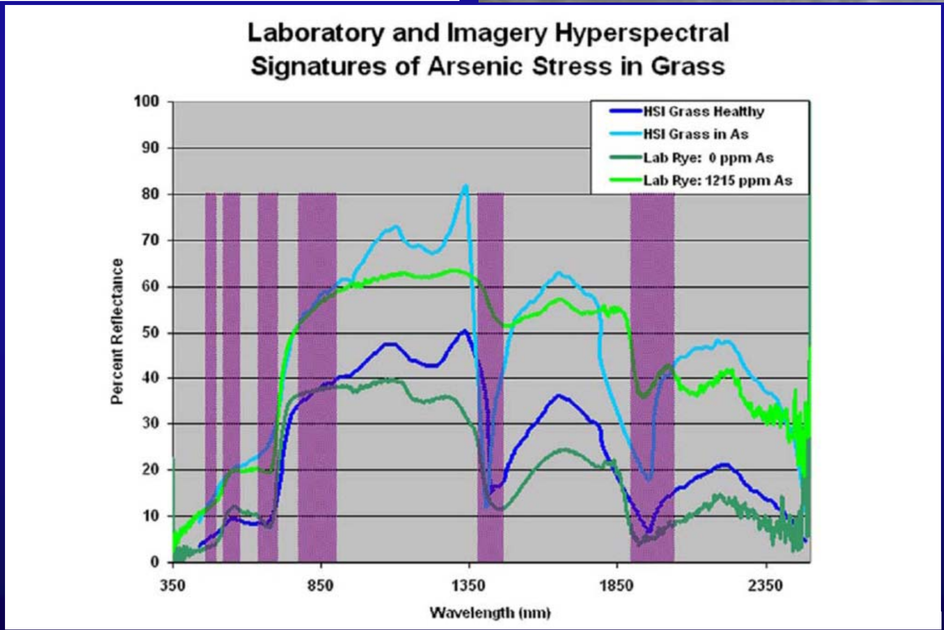
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Spectral Wavelengths and their Importance in the Study of Vegetation Stress

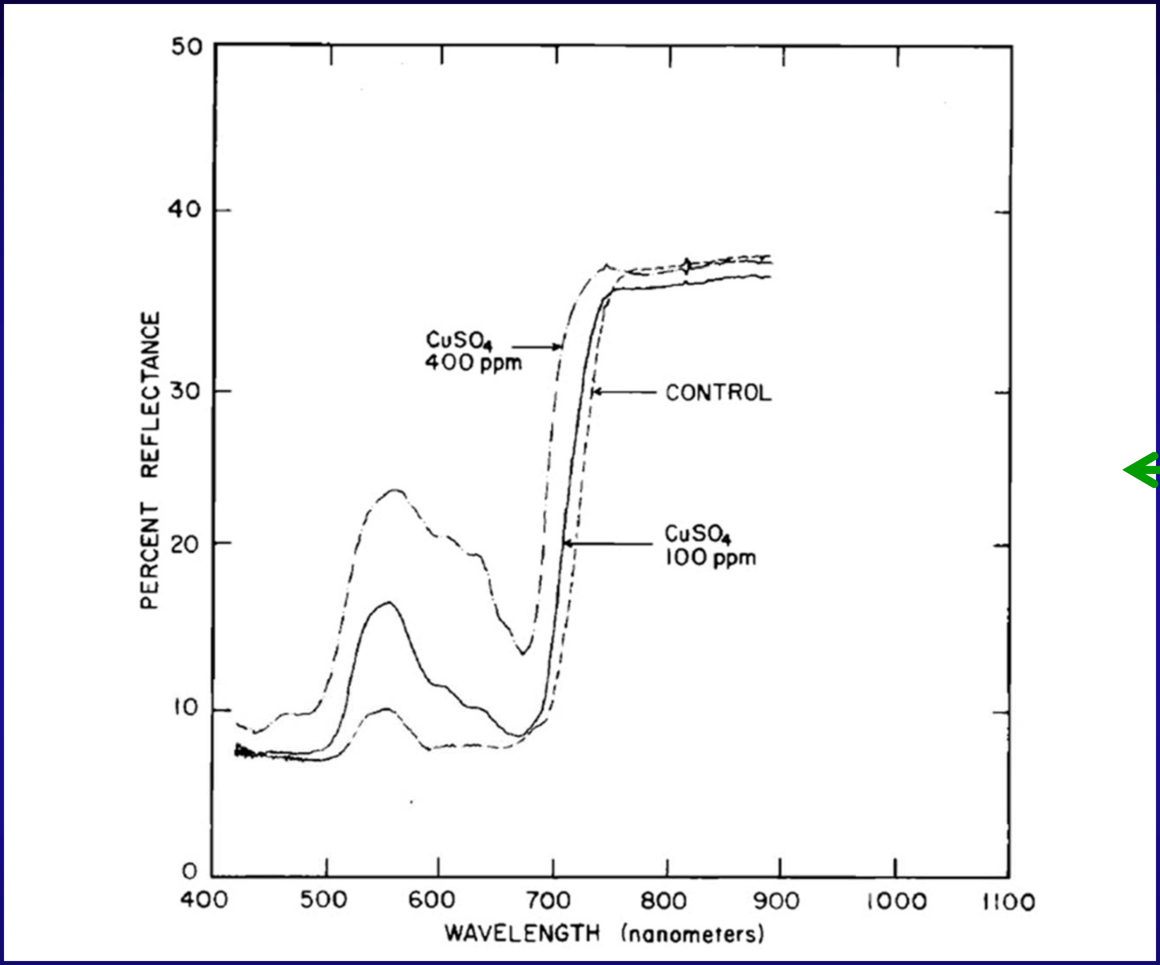




See chapter 23

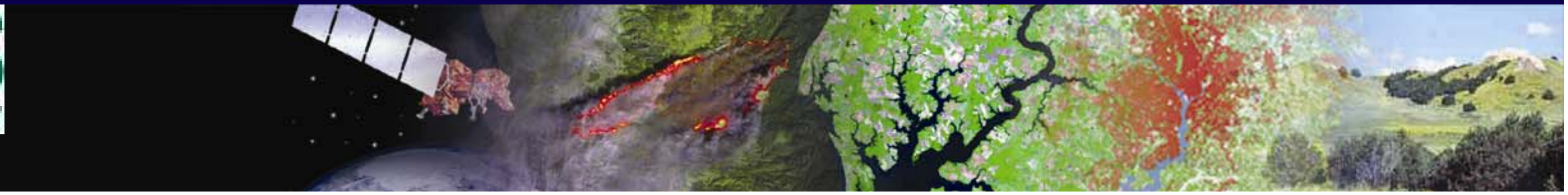
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Spectral Wavelengths and their Importance in the Study of Vegetation "blue shift" and "red shift" due to stress

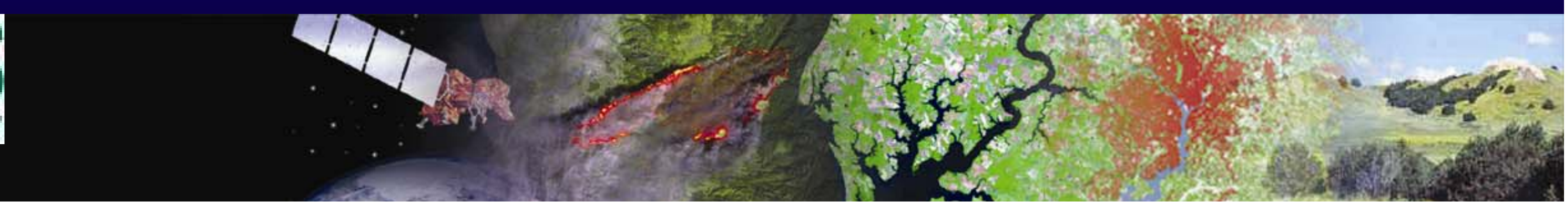


The "blue" shift in the Red-Edge in laboratory-grown sorghum exposed to different levels of copper sulfate in the soil.

Note: see chapter 23

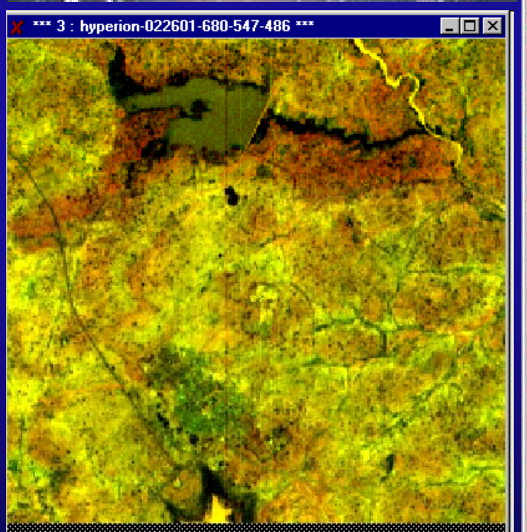


Hyperspectral Image Data Composition
Mega-file Data Cube (MFDC)



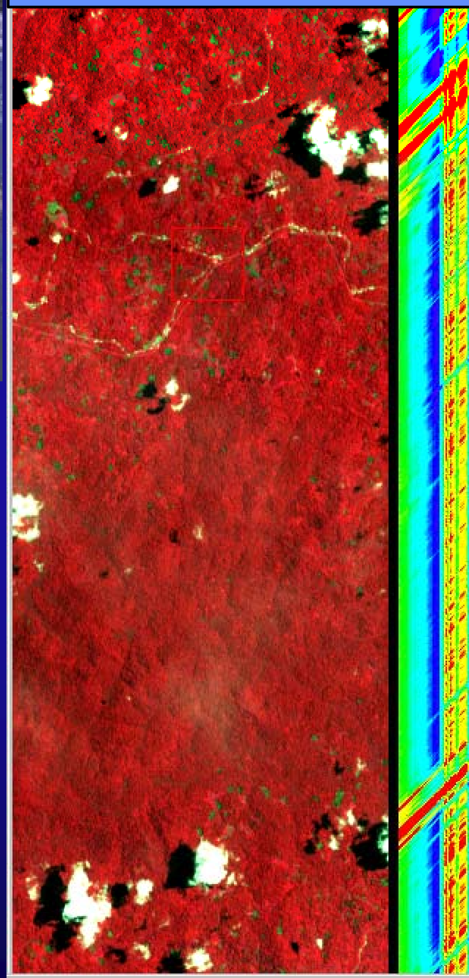
Advanced Hyperspectral Remote Sensing of Terrestrial Environment

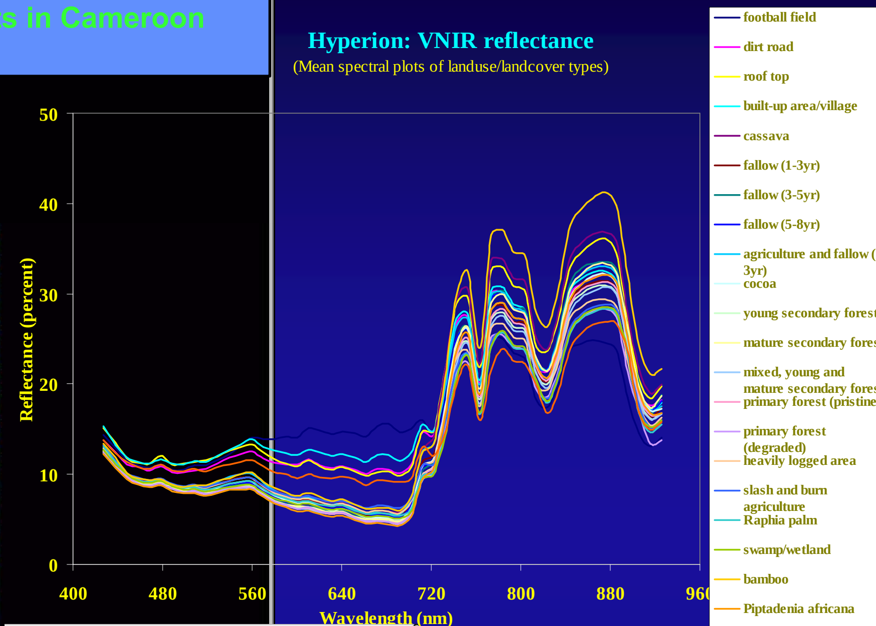
Mega file Data Cube (MFDC) of Hyperion Sensor onboard EO-1

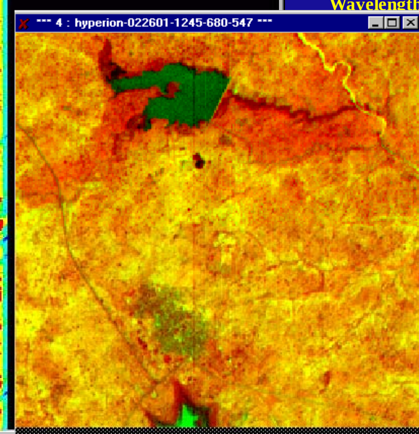


FCC (RGB): 680, 547, 486

e.g., MFDC of African Rainforests in Cameroon







Hyperion has 220 bands in 400-2500 nm

Note: Currently NASA is planning a next Spaceborne Hyperspectral mission called: HyspIRI

FCC (RGB): 1245, 680, 547

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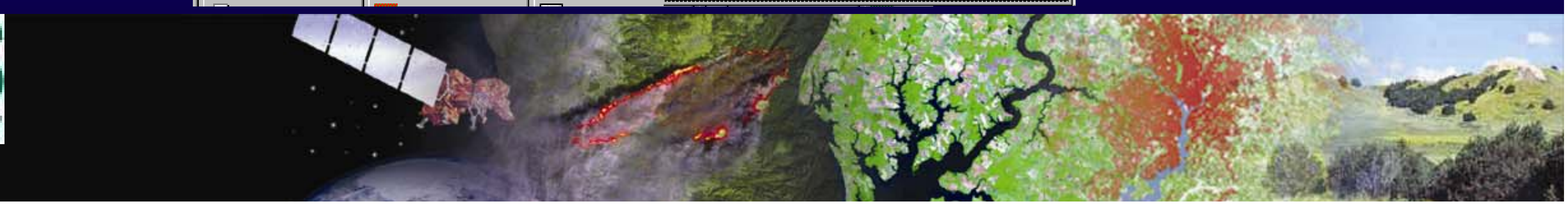
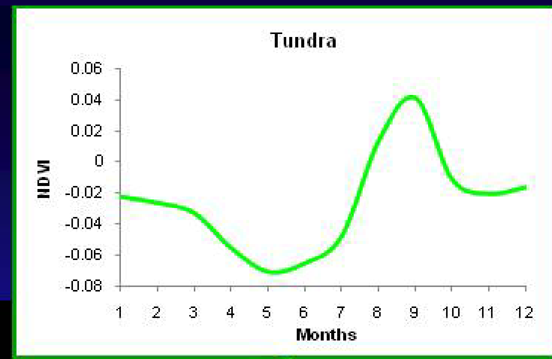
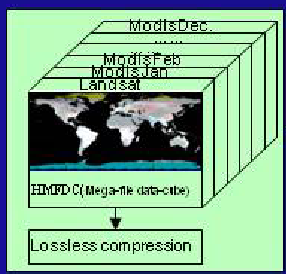
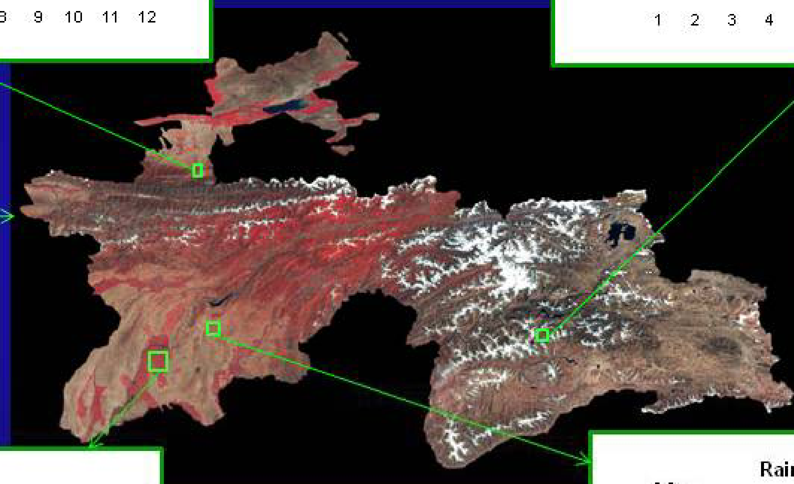


Advanced Hyperspectral Remote Sensing of Terrestrial Environment

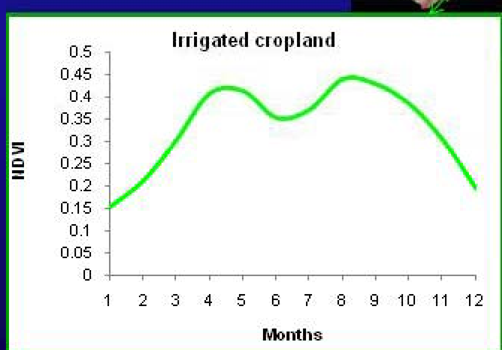
Mega file Data Cube (MFDC) of Landsat (top layer) and MODIS timeseries (spectral profile)

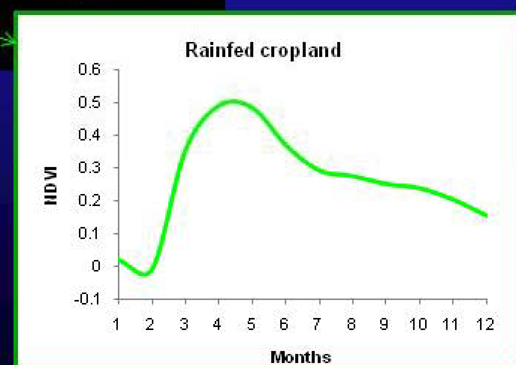


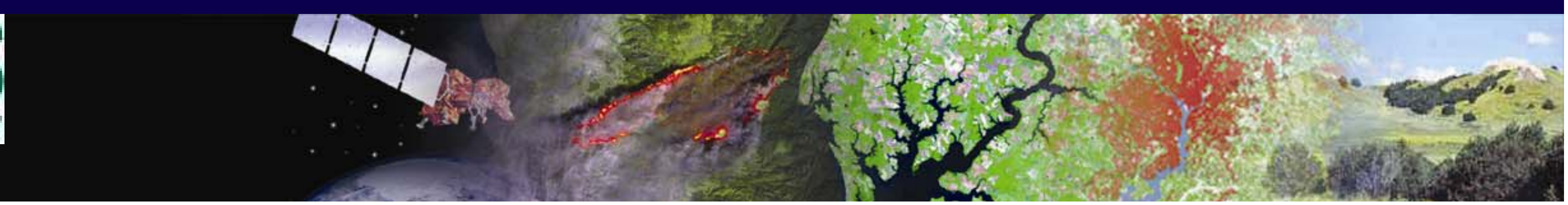




Note: A MFDC can have 100's or 1000's of bands from same sensor or different sensors or sensor data and other spatial data. **Example shown here**: Landsat (top layer) and MODIS time series (spectral profile).





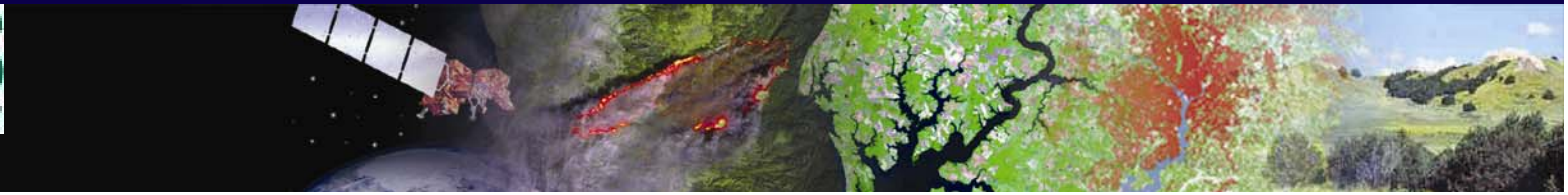


It is important to note that upcoming hyperspectral missions can serve not only as a means of detailed and highly precise characterization of terrestrial vegetation,

but also as a

spaceborne reference for establishing multi-sensor continuity and compatibility among current, past, and future multi-spectral sensors.

Note: see chapter 26, Miura et al.



Advanced Hyperspectral Remote Sensing of Terrestrial Environment

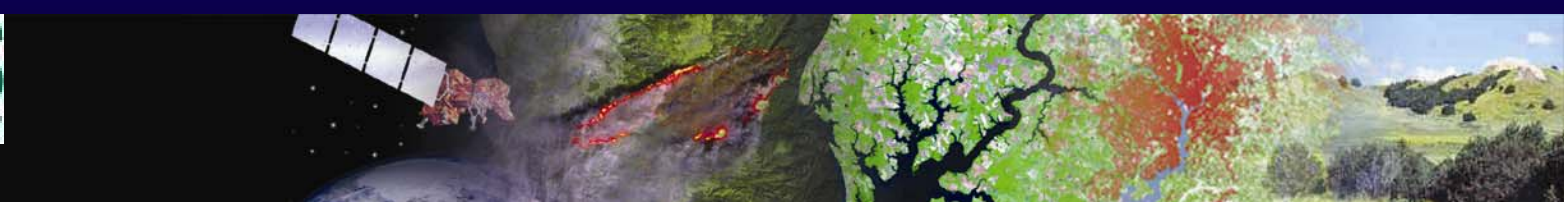
Hyperspectral Data in Long-term inter-sensor Calibration and Continuity Studies

Specific issues of multi-sensor VI continuity that can be addressed with hyperspectral remote sensing include the following:

1. **Spectral:** a large number of narrow spectral bands that continuously cover the visible, nearinfrared, shortwaveinfrared wavelength regions can be spectrally convolved to simulate spectral responses of virtually any broadband sensors. The simulated data can be used for multi-sensor comparisons devoid of mis-registration. It should be noted that, although the word, "simulation," is used here, the resultant, spectrally aggregated values are actual observations.

2. **Spatial:** current and future hyperspectral sensors provide medium resolution images (4–60 m spatial resolution with 30 m being typical) with swaths of 3–150 km with 30 km being typical. These resolutions are fine enough and these swath widths are wide enough to allow simulation of various pixel footprint sizes via spatial aggregation. The aggregated data can be used to examine VI compatibility across multiple resolutions.

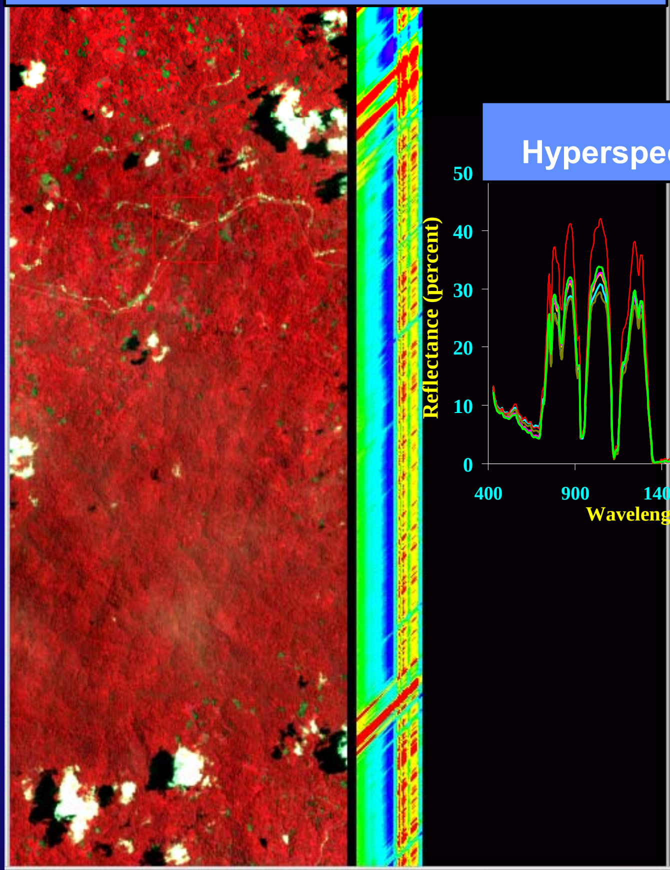
Note: see chapter 26, Miura et al.



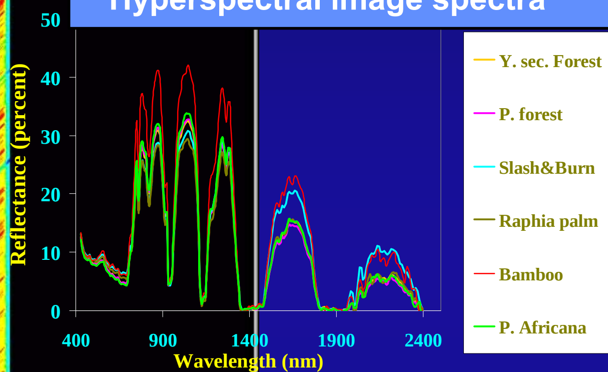
Hyperspectral Narrowband Sensors (imaging Spectroscopy) Generating data for other Sensors?

Processing acquired hyperspectral data into other types of data

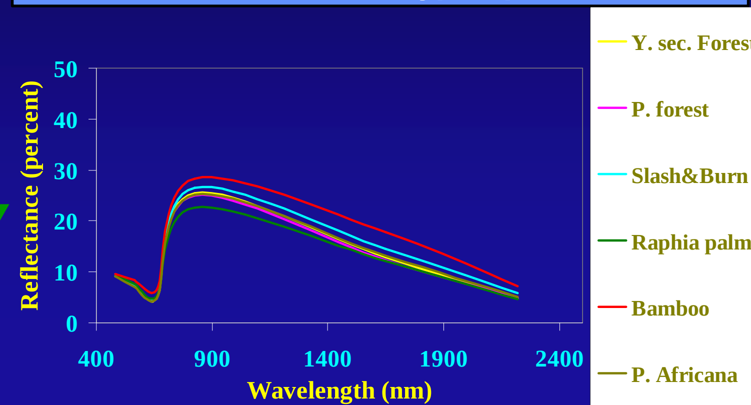
Hyperspectral image data cube



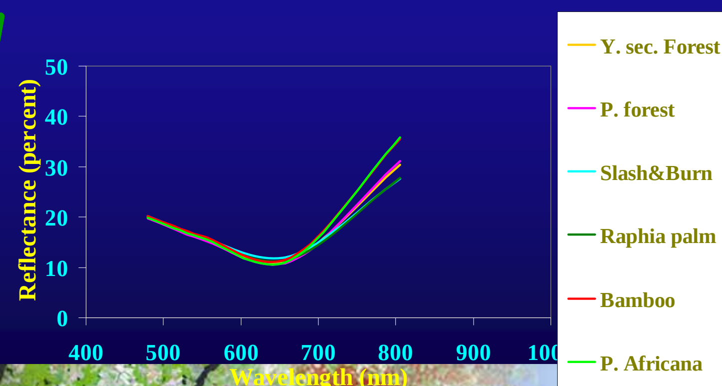
Hyperspectral image spectra



Generated Landsat ETM+ for data continuity: 6 non-thermal broadbands at 30 m of Landsat ETM+ Generated from a Hyperspectral Sensor



Generated IKONOS 4 m data: 4 broadbands at 4 m of IKONOS Generated from a Hyperspectral Sensor



Imaging spectroscopy: 242 hyperspectral bands, each of 5 or 10 nm wide, in 400-2500 nm spectral range.

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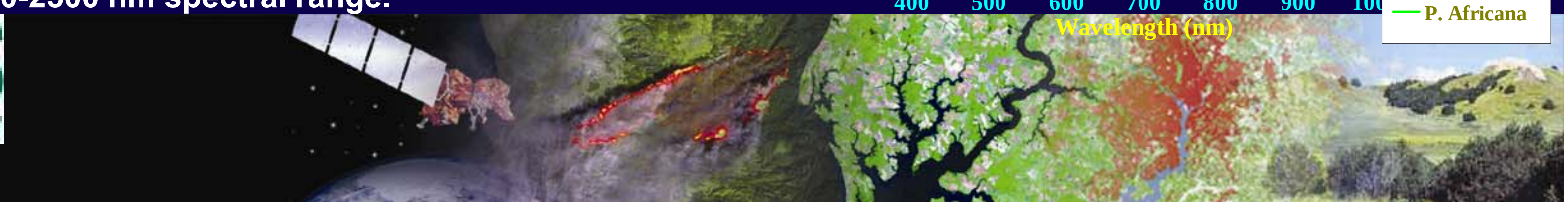
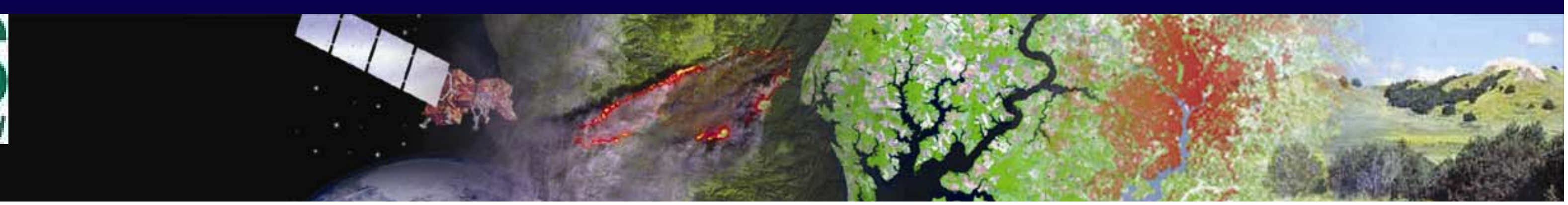


Advanced Hyperspectral Remote Sensing of Terrestrial Environment

Acquiring Spectral Signatures



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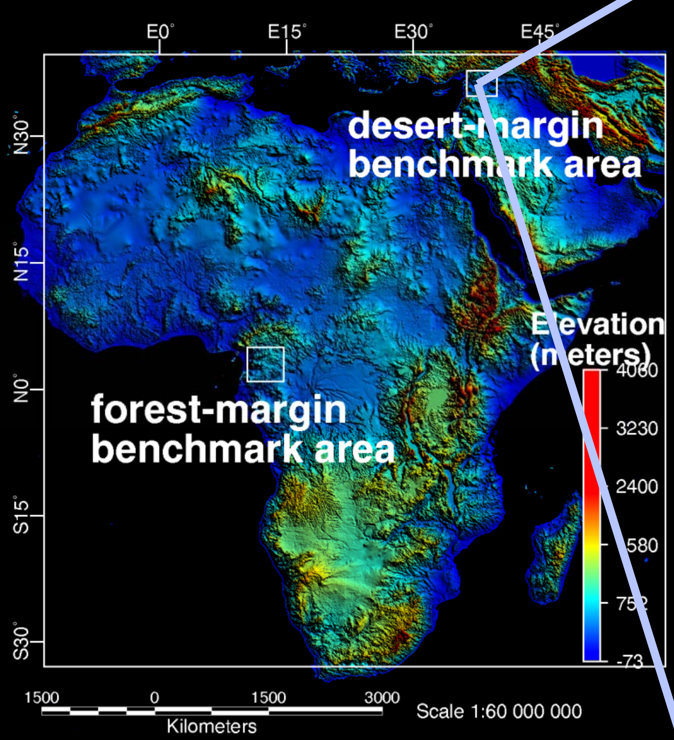
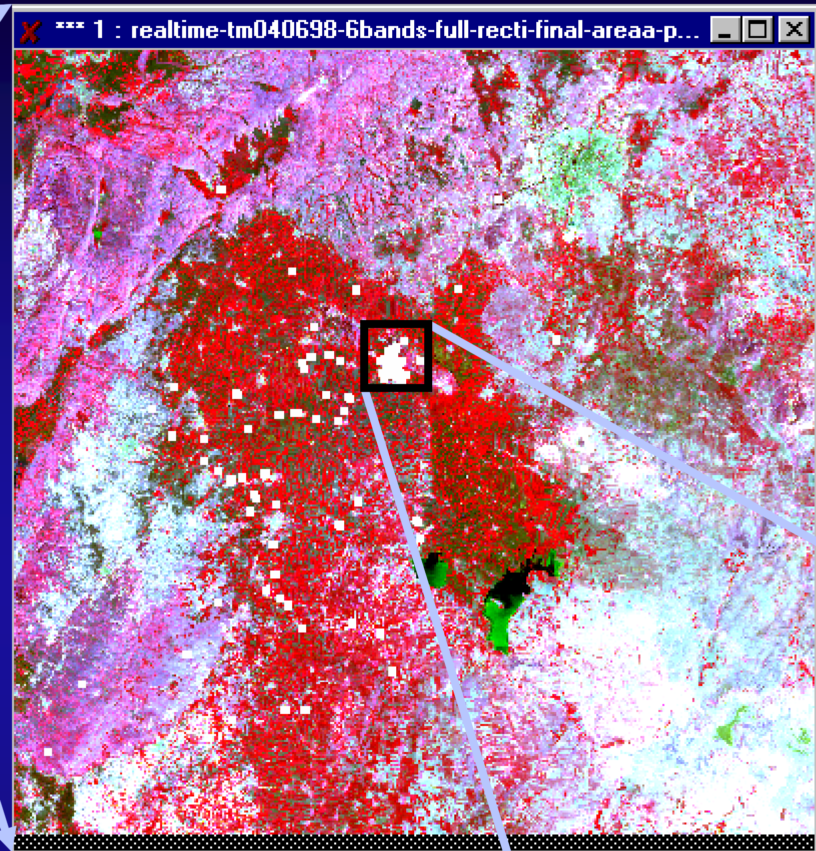
Hyperspectral Data on Vegetation from

A Desert-Margin Benchmark Area

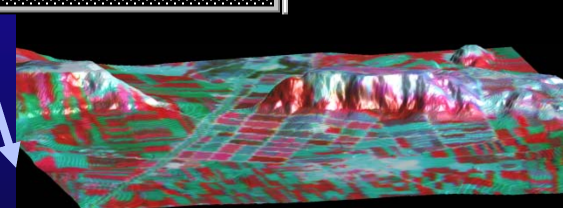


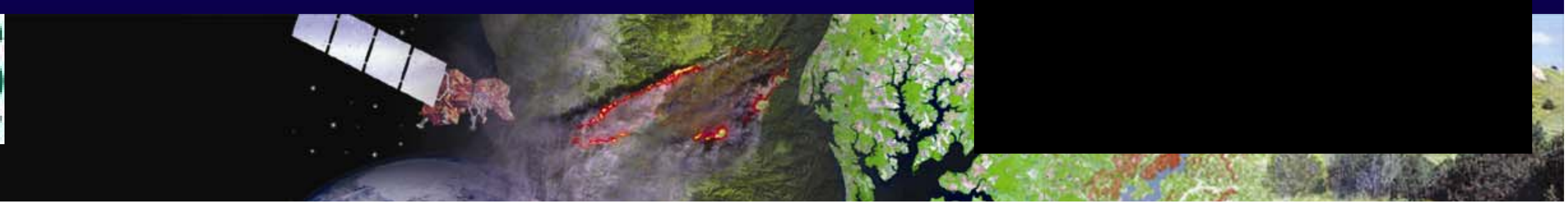
<u>Forest-margin</u>: Rainforest vegetation characteristics studied using Hyperion Spaceborne Hyperspectral Data



About 50 km by 50 km (part of Landsat-5 TM Path: 174, Row: 35)

<u>Desert-margin</u>: Agricultural cropland vegetation characteristics studied using Hand-held Spectroradiometer Hyperspectral Data





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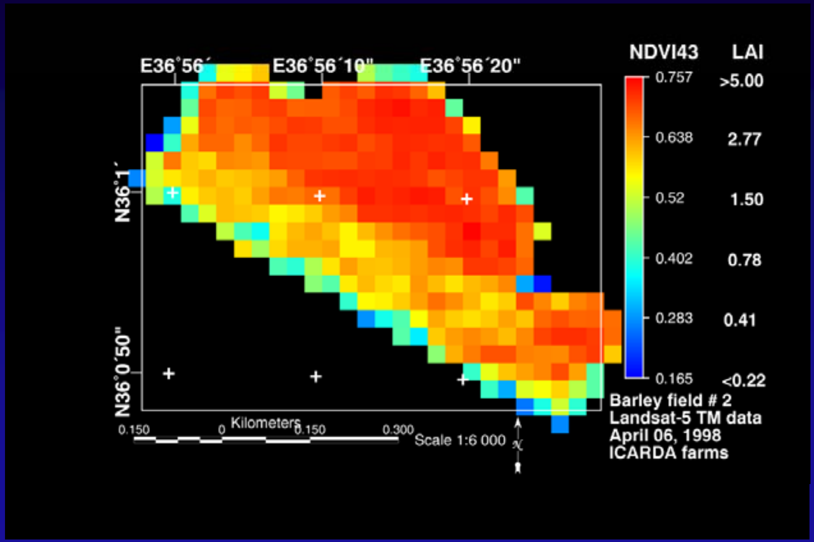
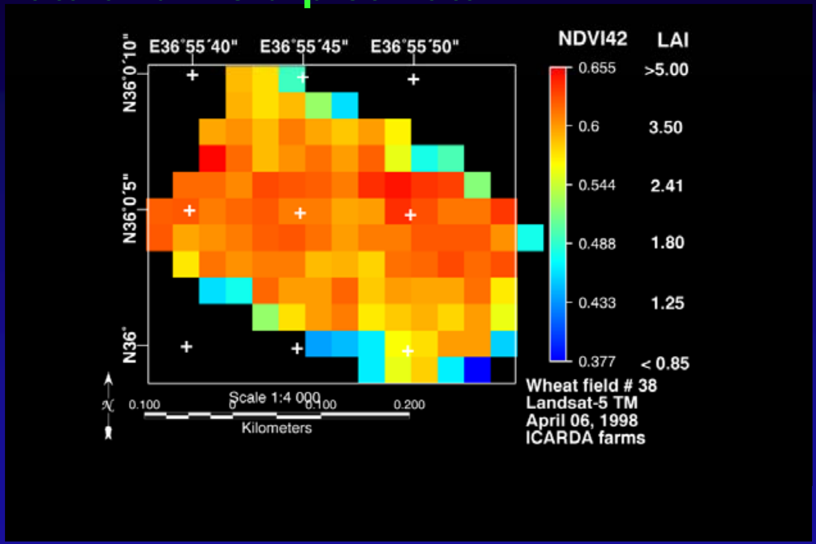
Wheat Versus Barley Crops

Broad-band Landsat TM Data and Field-plot Data



Barley field # 2 NDVI43 and LAI



wheat field # 38 NDVI42 and LAI

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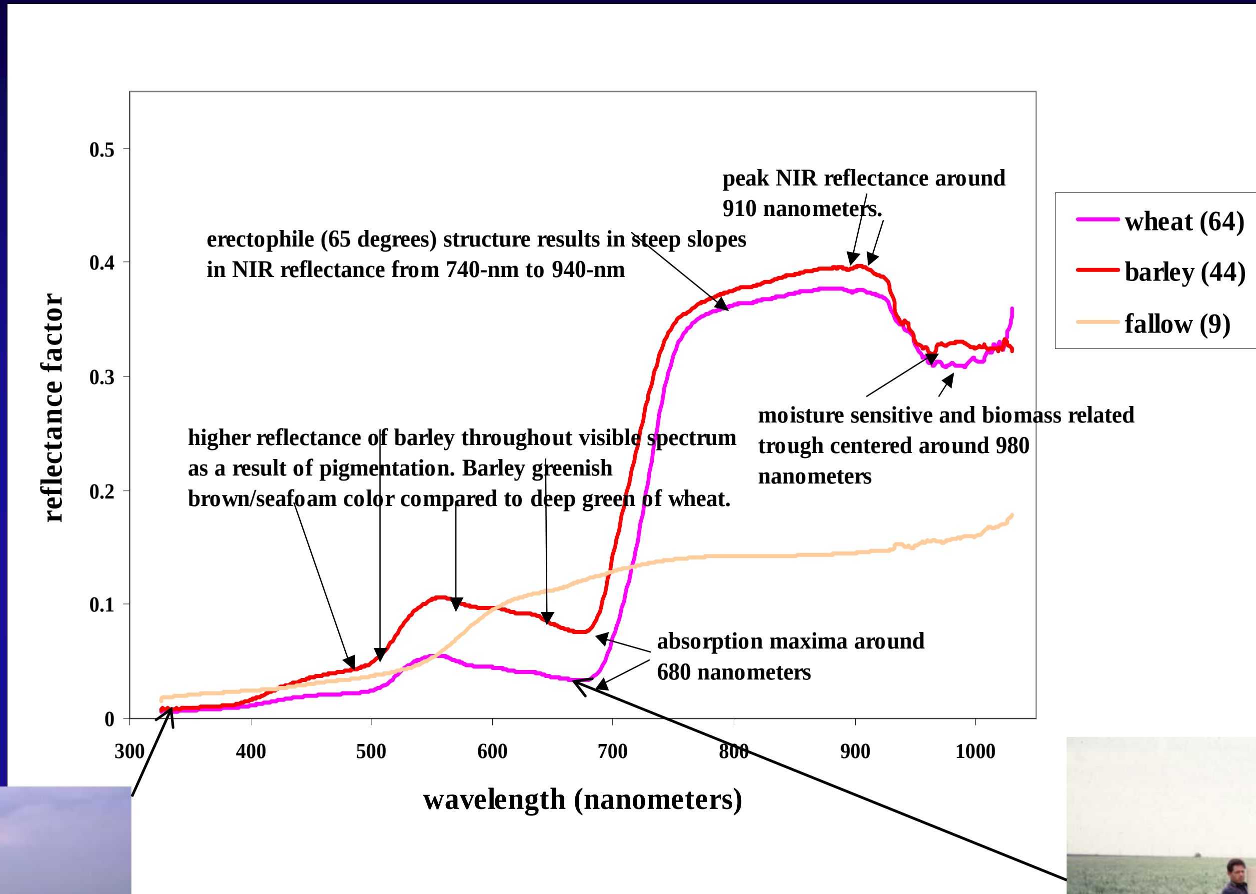
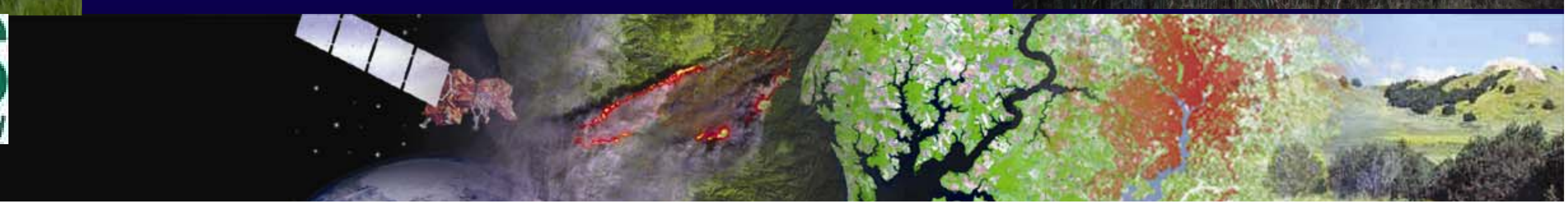
Wheat Crop Versus Barley Crop Versus Fallow Farm

Hyperspectral narrow-band Data for an Erectophile (65 degrees) canopy Structure





Hyperspectral Data on Agricultural Crops Gathered for Following Crops

Illustrations of Crop Growth Stages for Some Leading World Crops

(a) Barley (*Hordeum vulgare)*

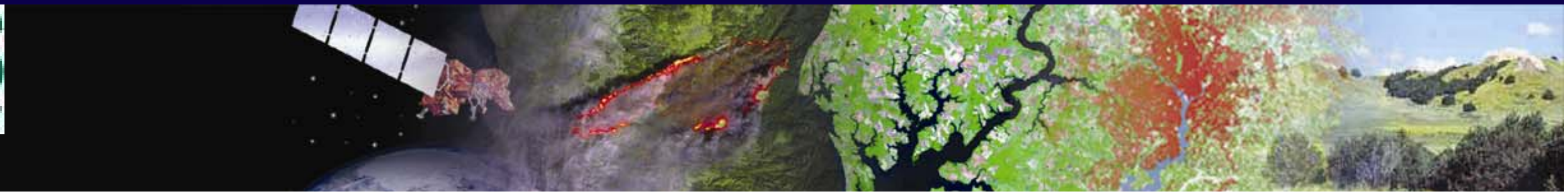
(b) Wheat (Triticum aestivum or durum)

(c) Lentil (Lens esculenta or Lens oriental)

(d) Vetch (Vicia narbonensis)

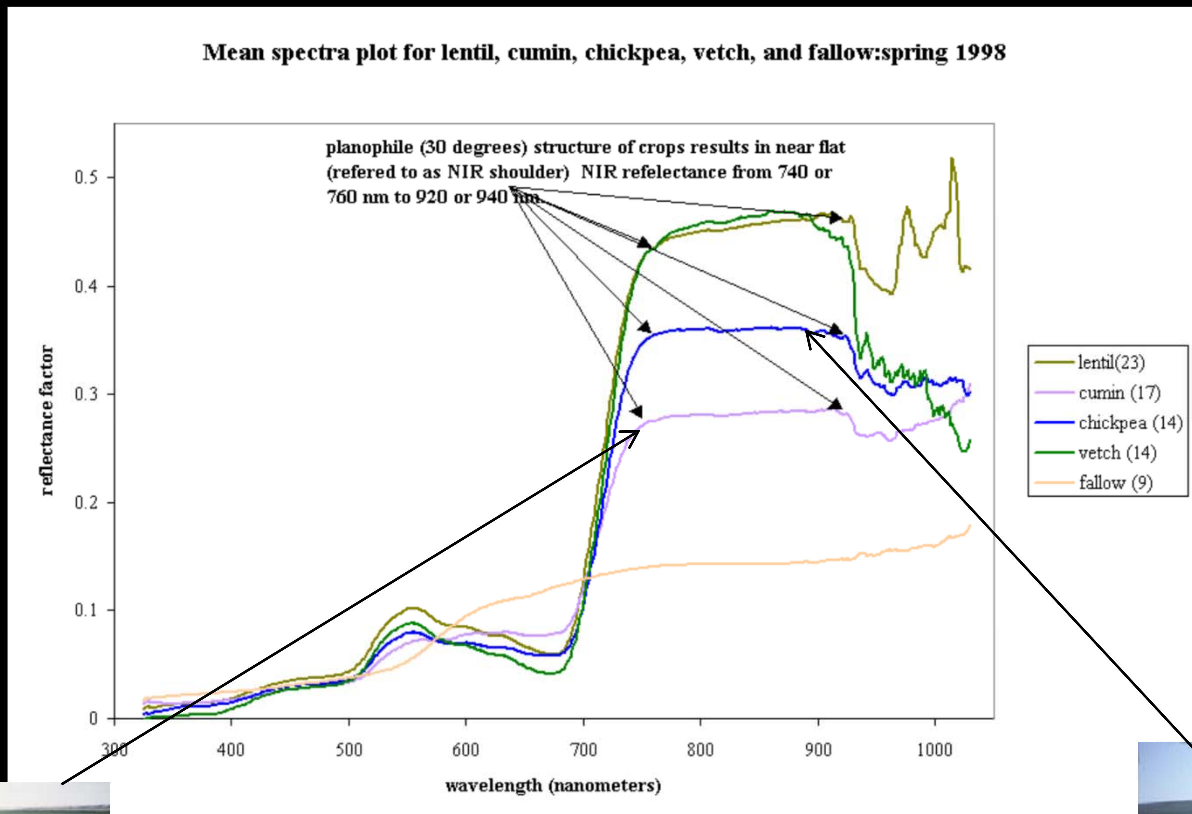
(e) Cumin (Cuminum cyminum)

(f) Chickpea (Cicer arietinum)



Wheat Crop Versus Barley Crop Versus Fallow Farm

Hyperspectral narrow-band Data for an Planophile (30 degrees) canopy Structure



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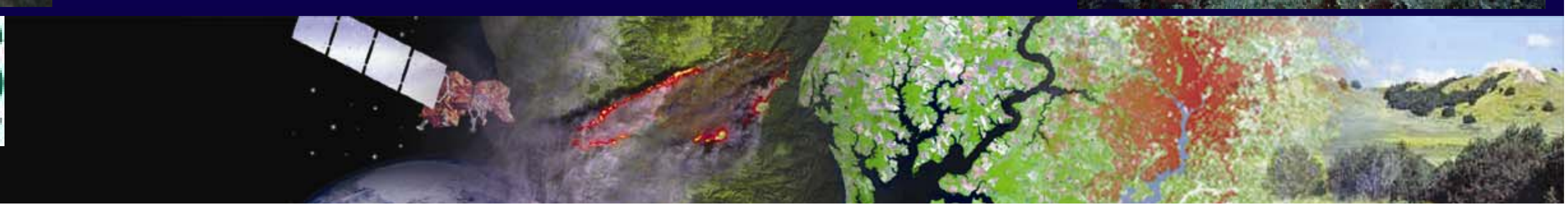
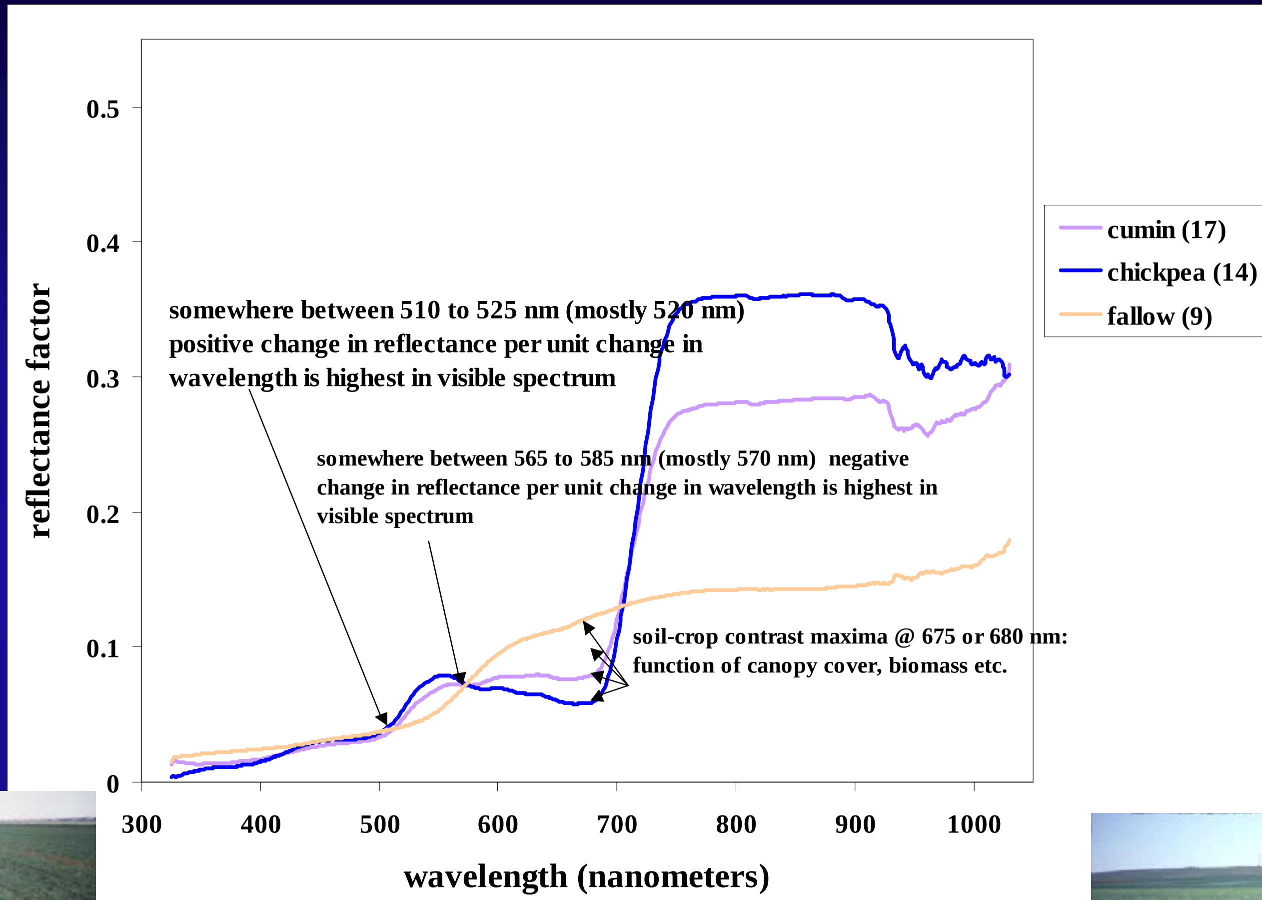


Cumin Crop Versus Chickpea Crop Versus Fallow Farm

Hyperspectral narrow-band Data



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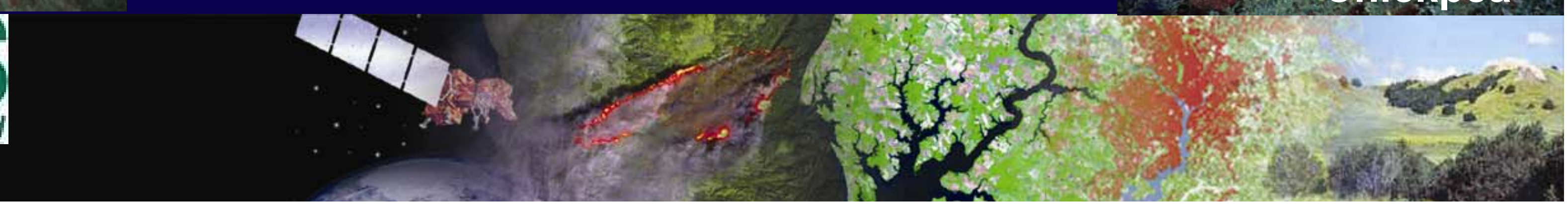
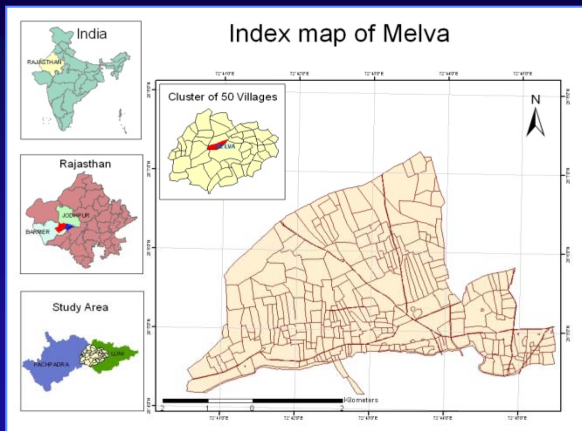
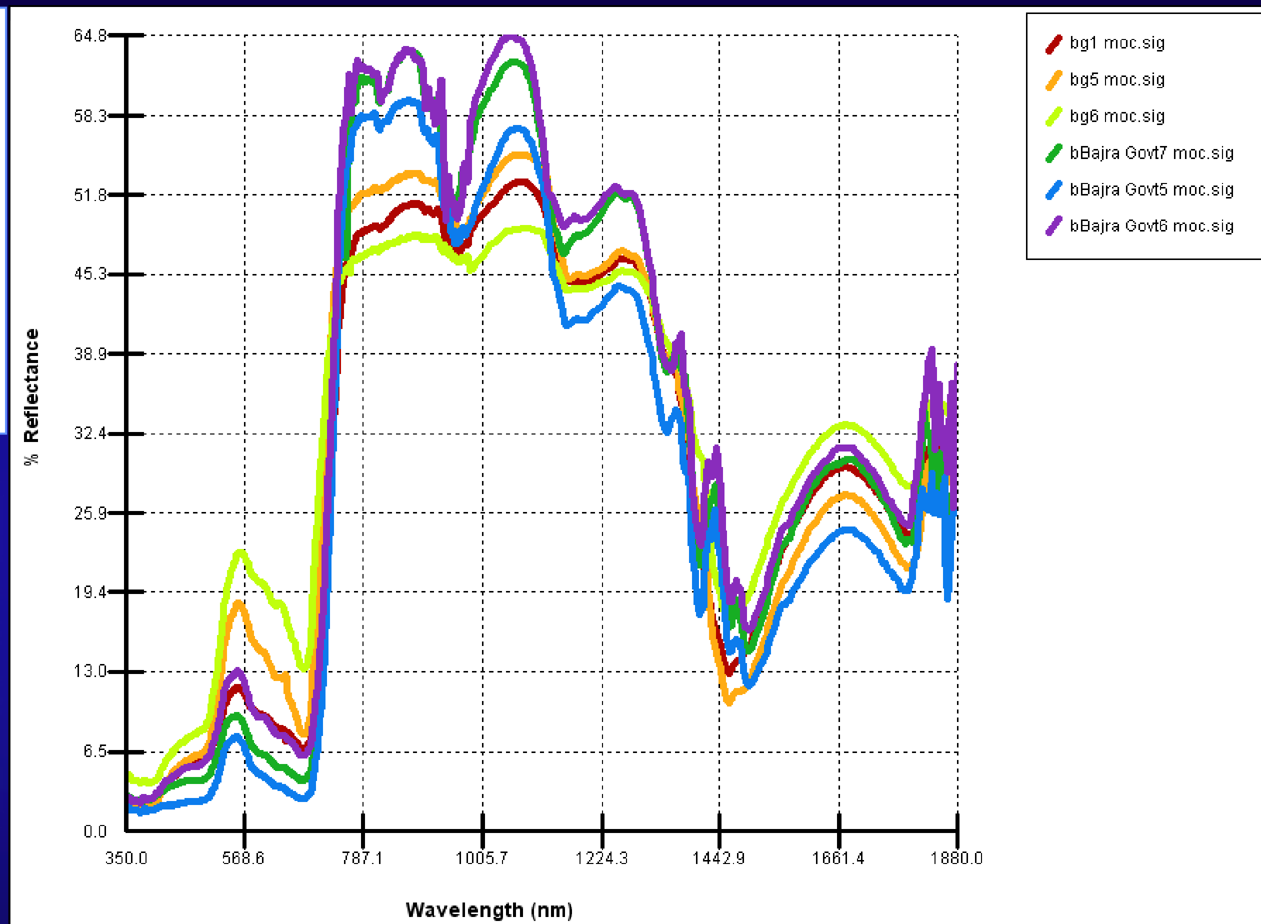


Hyperspectral Data on Agricultural Crops

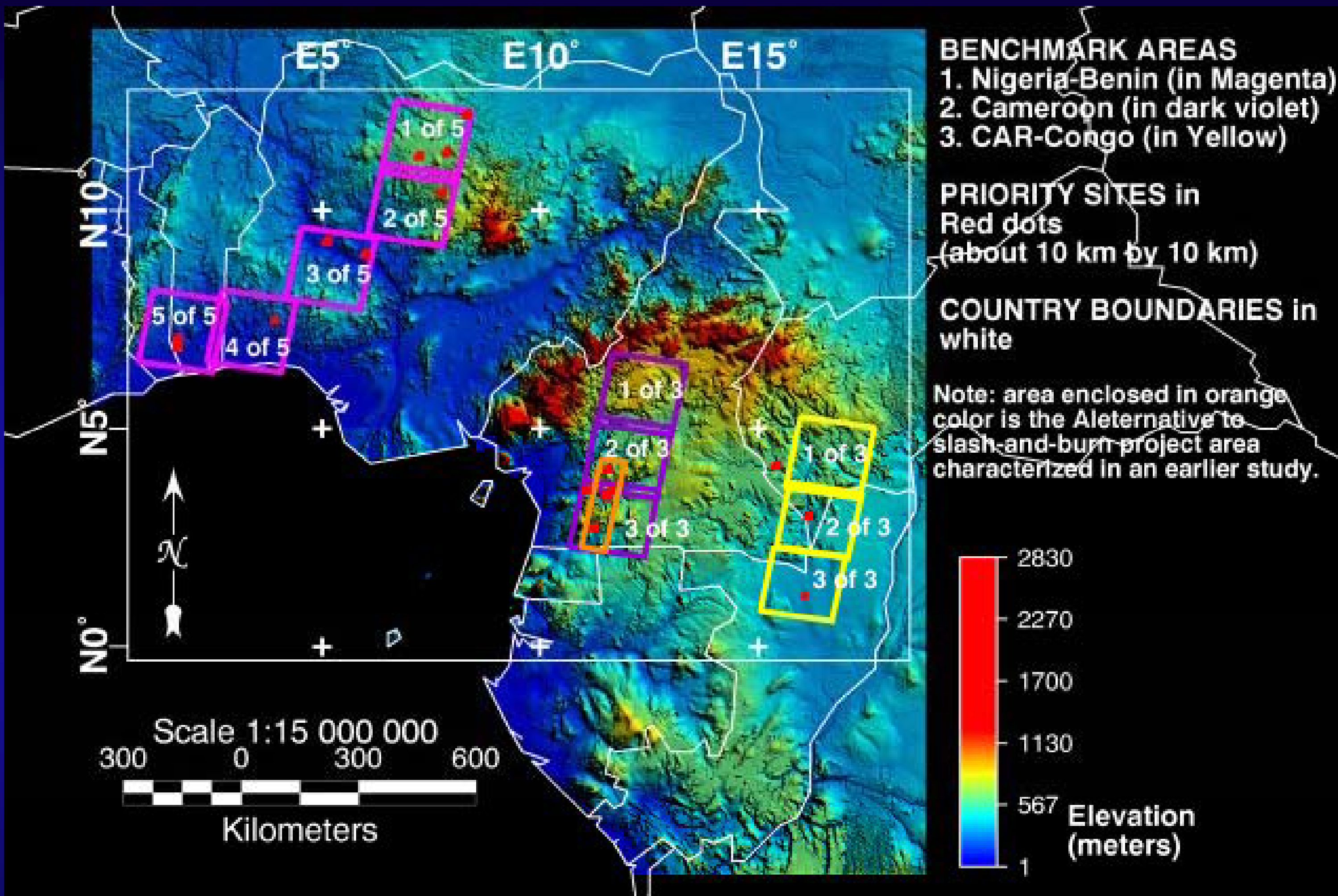
Data for Some of other the Major World Crops in the Semi-arid Environment



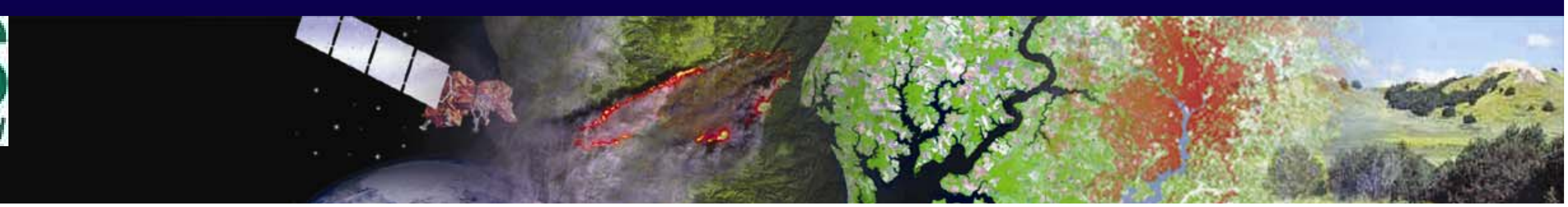


Hyperspectral Data on Vegetation from

A Forest-Margin Benchmark Area



<u>African savannas and Rainforests</u>: Wide range of vegetation including forest and savanna vegetation and agricultural crops studies using Hyperion and Spectroradiometer data.



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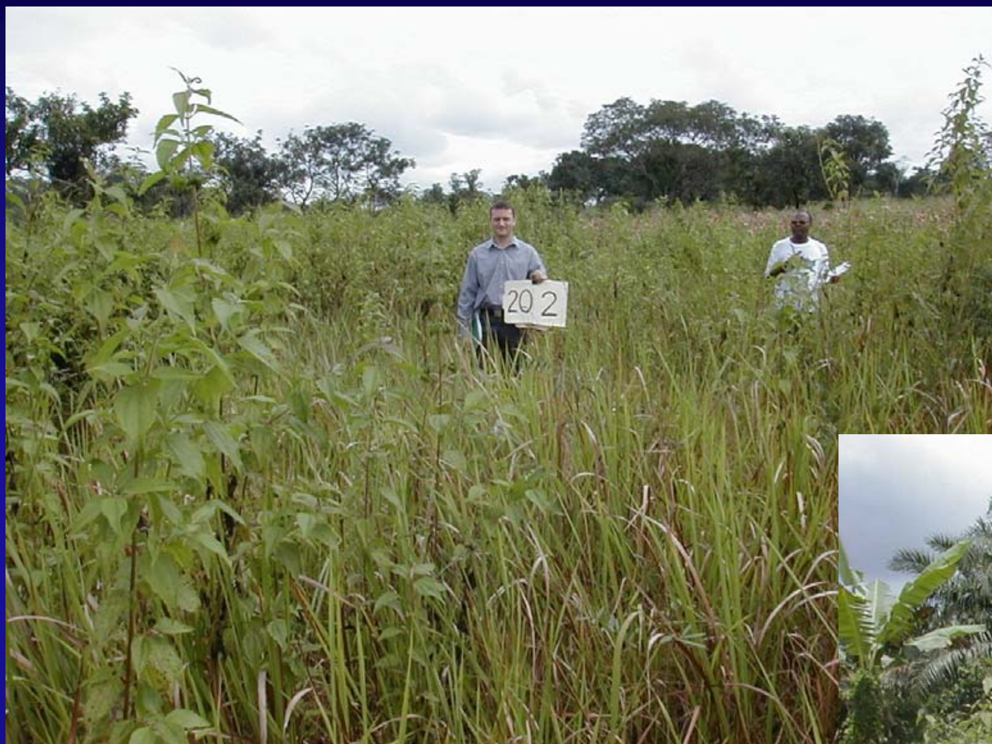
Hyperspectral Data Gathered for Two Dominant Weeds

Illustrations of Weeds in Africa Savannas and Rainforests

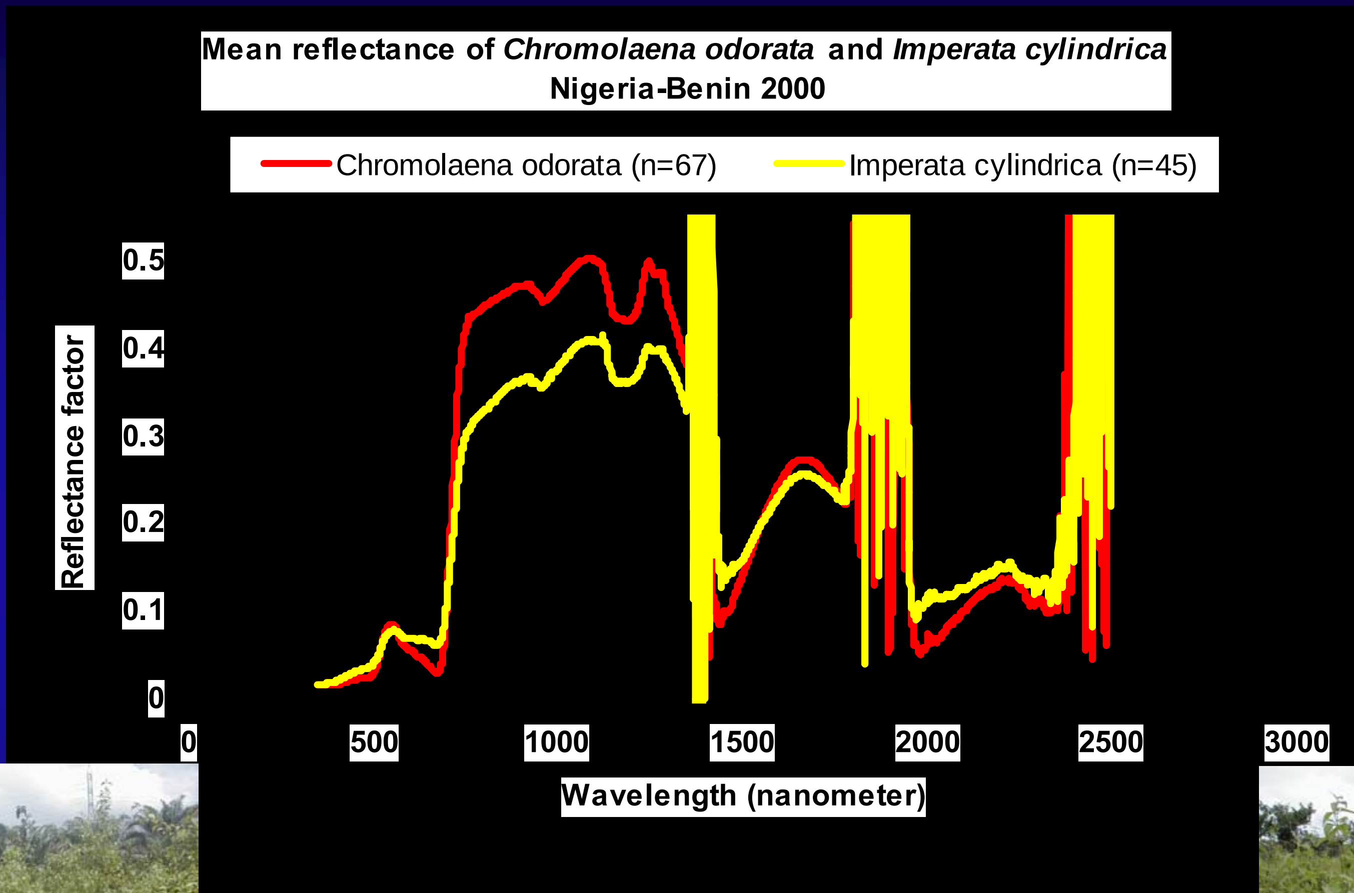


Imperata cylindrica in African Savanna

Chromolaena odorata in African Rainforests

Hyperspectral Data of Two Dominant Weeds

Chromolaena Odorata in African Rainforests vs. *Imperata Cylindrica* in African Savannas



Chromolaena Odorata

Imperata Cylindrica

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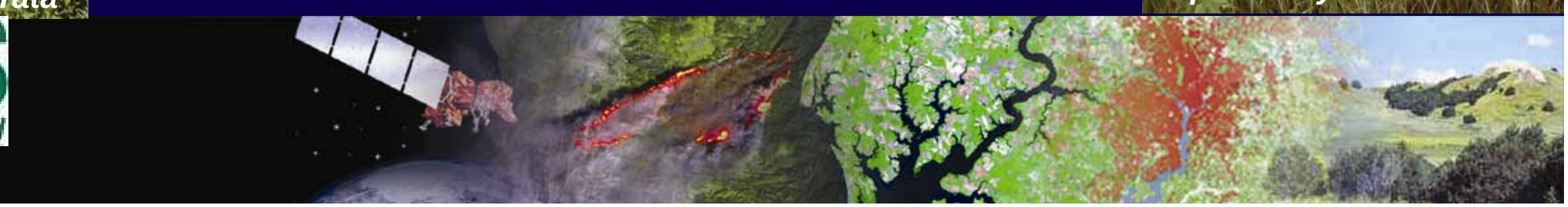
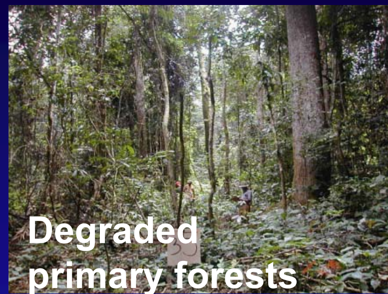
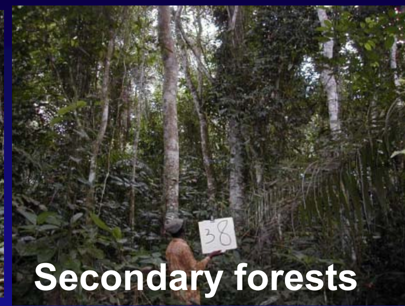
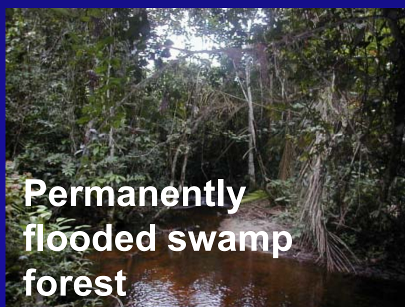


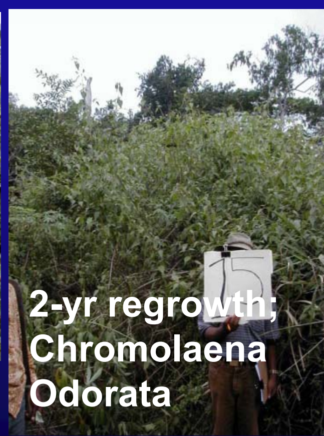
Hyperspectral Data Gathered for the Following Rainforest Vegetation

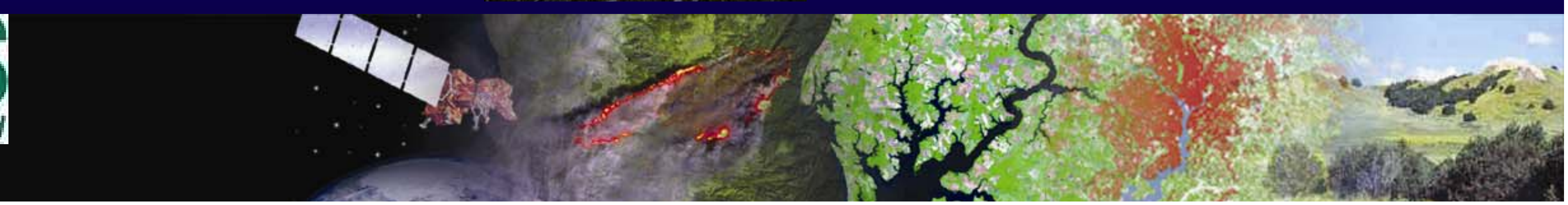
using Hyperion EO-1 Data and Field-based Measurements of Biophysical Characteristics





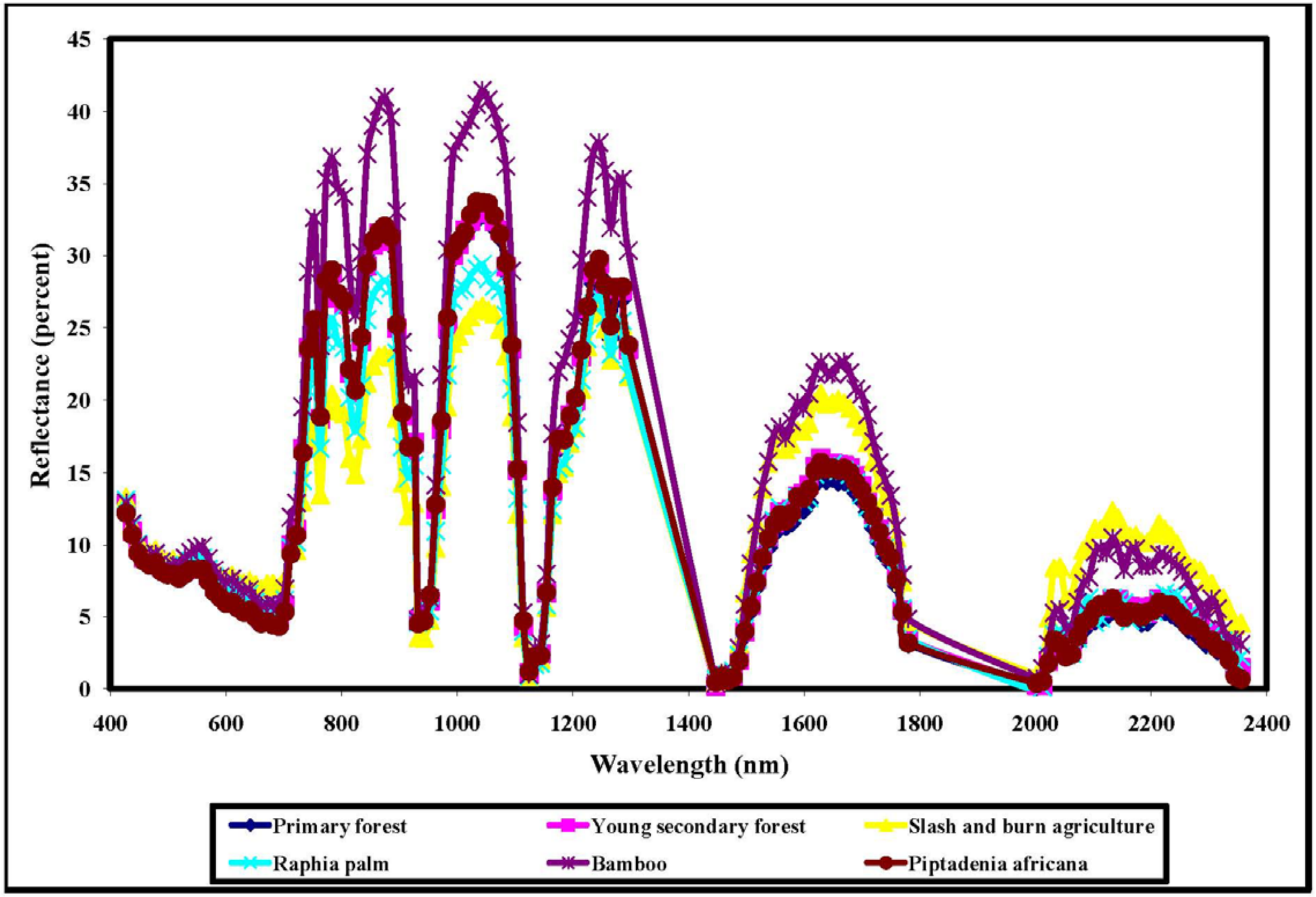


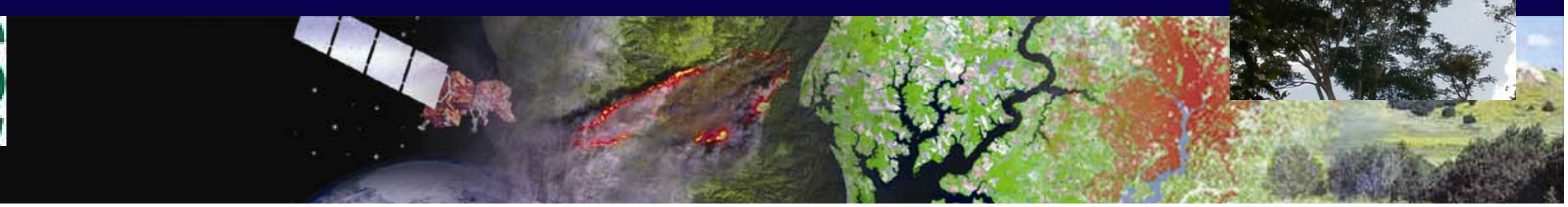




Hyperspectral Data Gathered for the Following Rainforest Vegetation

using Hyperion EO-1 Data





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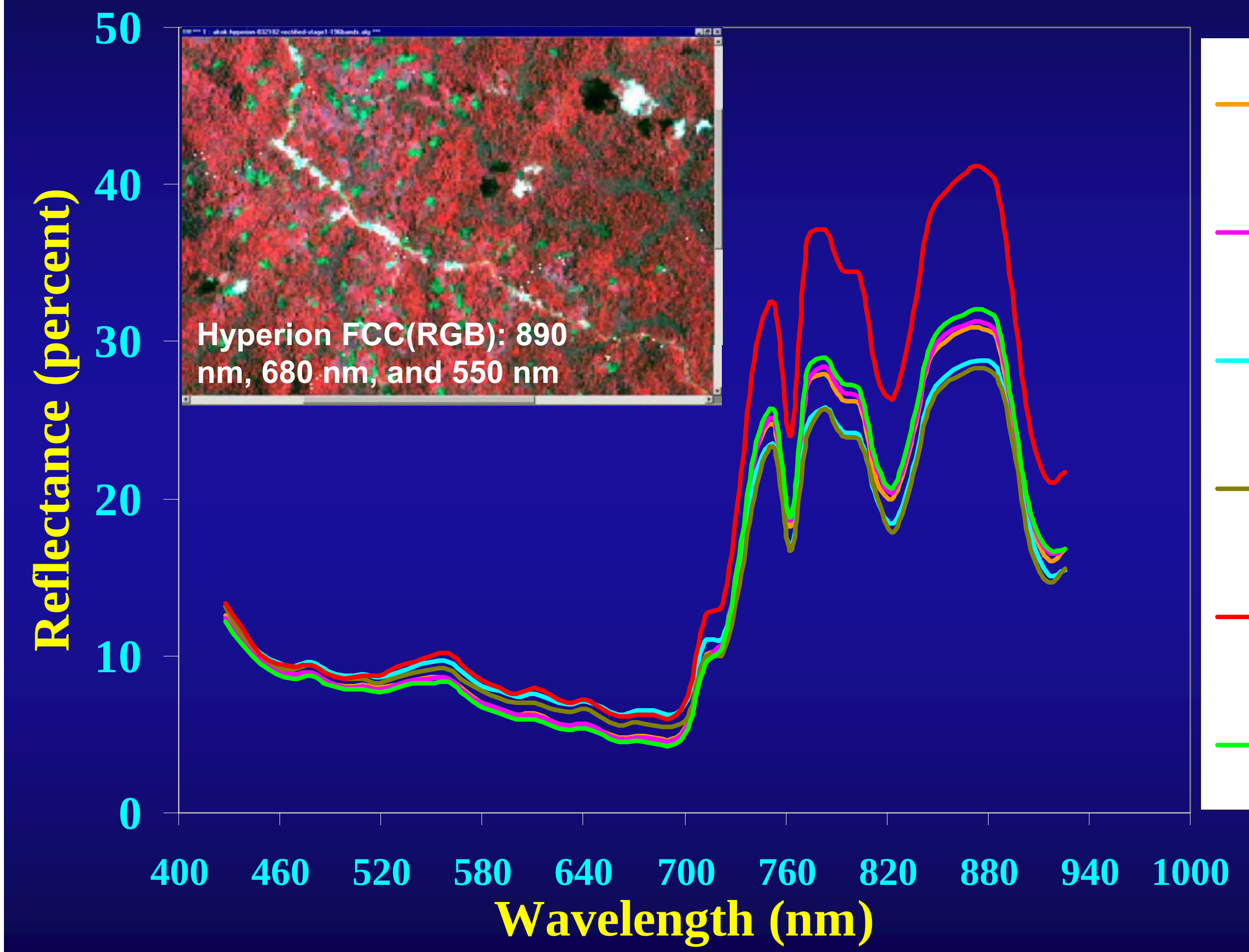
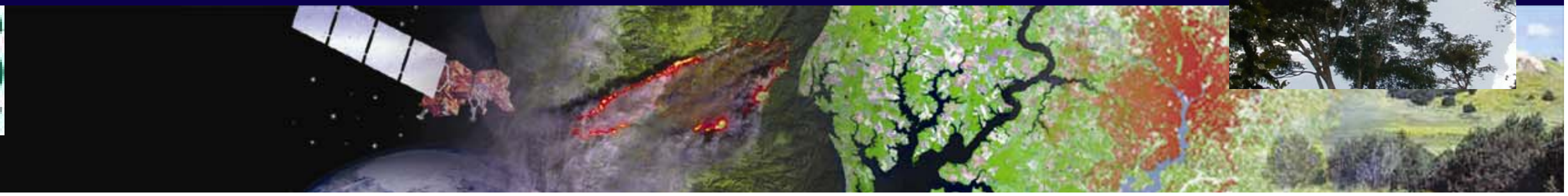
Hyperspectral Data Gathered for the Following Rainforest Vegetation

using Hyperion EO-1 Data





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Hyperspectral Data on Tropical Forests

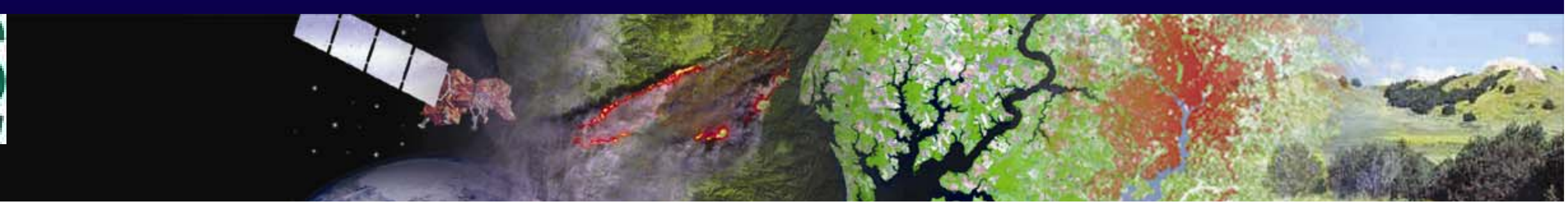
Factors Influencing Spectral Variation over Tropical Forests

1. Biochemistry (e.g., plant pigments, water, and structural carbohydrates):
Leaf reflectance in the visible spectrum is dominated by absorption features created by plant pigments, such as:

- **chlorophyll a (chl-a): absorps in 410-430 nm and 600-690 nm;**
- **chlorophyll b (chl-b): absorps in 450-470 nm;**
- **carotenoids (e.g., β-carotene and lutein): peak absorption in wavebands <500 nm; and**
- **anthocyanins.**
- **Lignin, cellulose, protein, Nitrogen: relatively low reflectance and strong absorption in SWIR bands by water that masks other absorption features**

……………However, dry leaves do not have strong water absorption and reveal overlapping absorptions by carbon compounds, such as lignin and cellulose, and other plant biochemicals, including protein nitrogen,starch, and sugars.

Note: see chapter 18, Clark et al.



Hyperspectral Data on Tropical Forests

Factors Influencing Spectral Variation over Tropical Forests

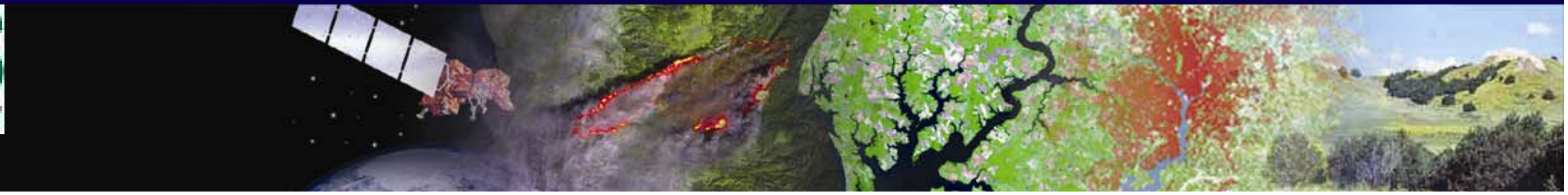
2. Structure or biophysical (e.g., leaf thickness and air spaces): of leaves, and the scaling of these spectral properties due to volumetric scattering of photons in the canopy;

3. Nonphotosynthetic tissues (e.g., bark, flowers, and seeds); and

4. Other photosynthetic canopy organisms (e.g., vines, epiphytes, and epiphylls) can mix in the photon signal and vary depending on a complex interplay of species, structure, phenology, and site differences,

……………………………..currently, none of which are well understood.

Note: see chapter 18, Clark et al.



Hyperspectral Data on Tropical Forests

Individual Tree Crown Delineation: Illustrated for 2 species

Figure 19.1

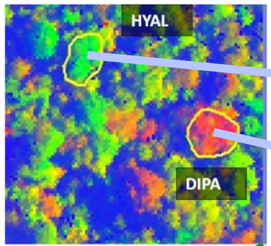


Figure 19.9

Figure. 19.2

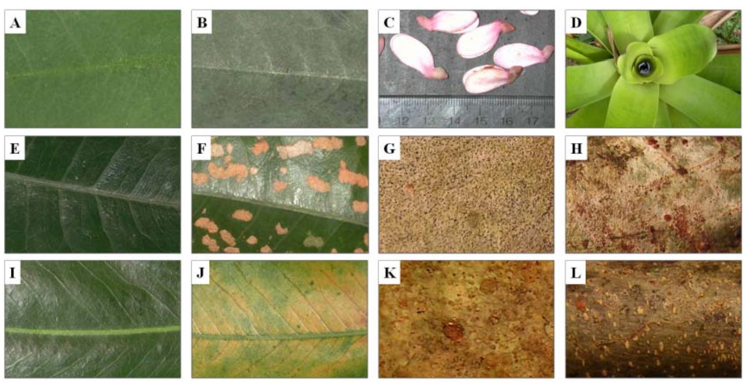
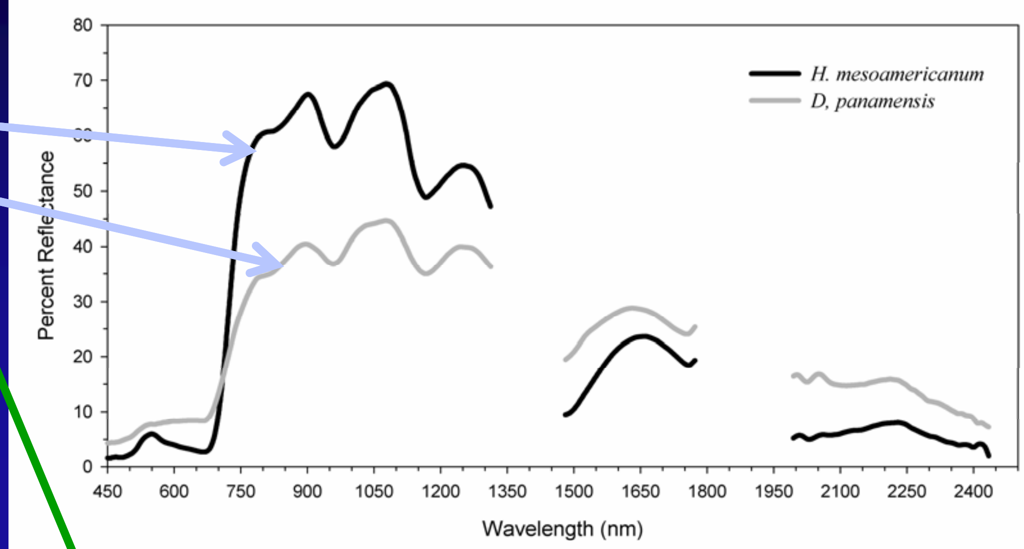


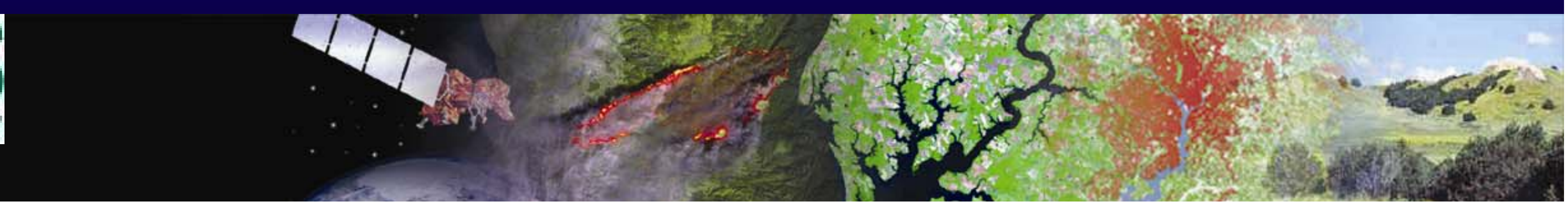
Figure. 19.3



"Fractional abundance of green vegetation (green), non-photosynthetic vegetation (red) and photometric shade (blue) from a spectral mixture analysis.

Individual tree crowns delineated with visual interpretation: *Dipteryx panamensis (DIPA) and Hyeronima alchorneoides (HYAL)."*

Note: see chapter 18, Clark et al.



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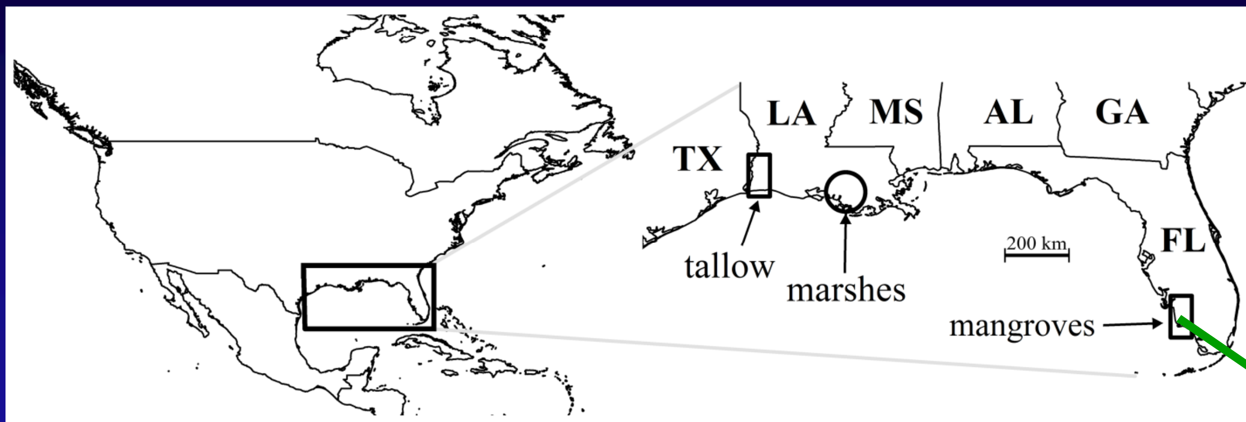
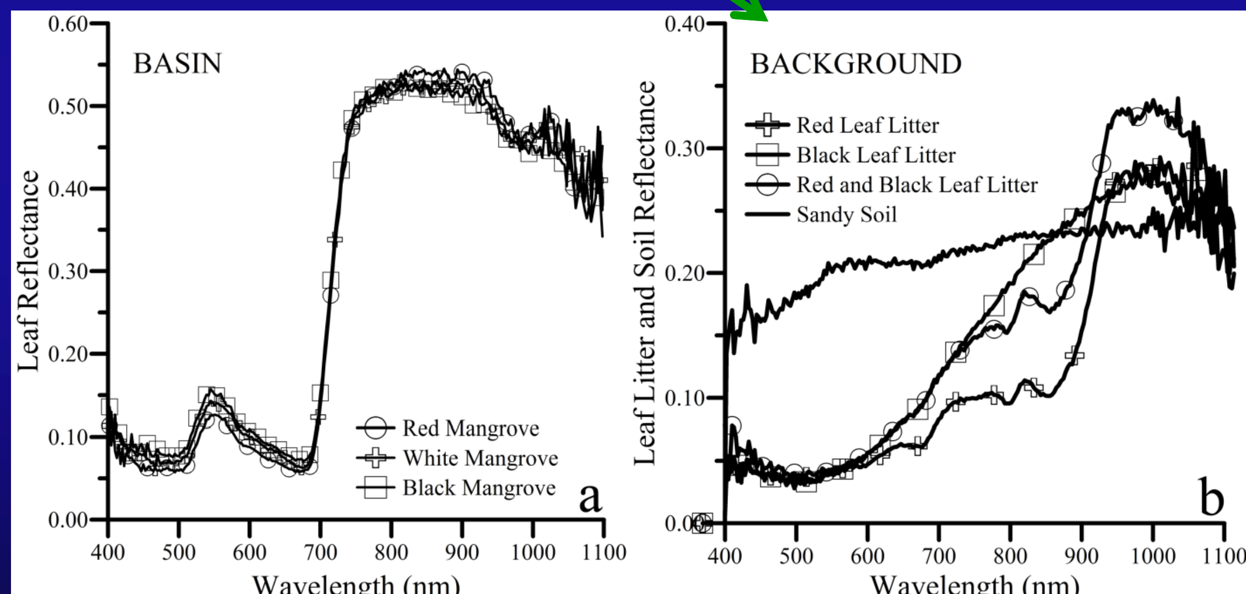
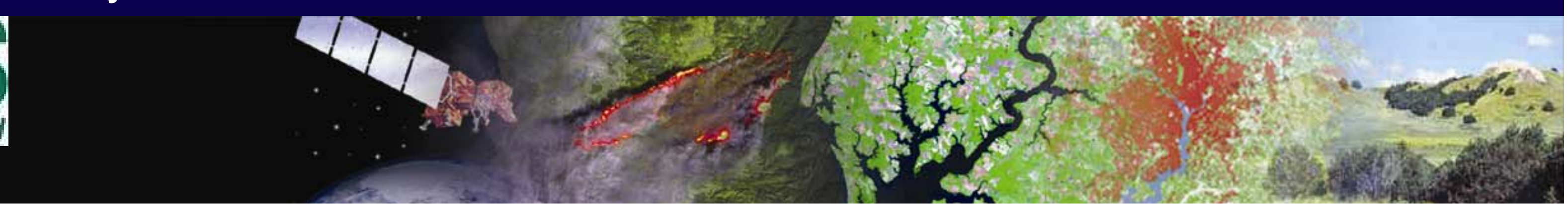
Hyperspectral Data on Tropical Forests

Hyperspectral Reflectance of Plant Litter in Mangroves Wetlands



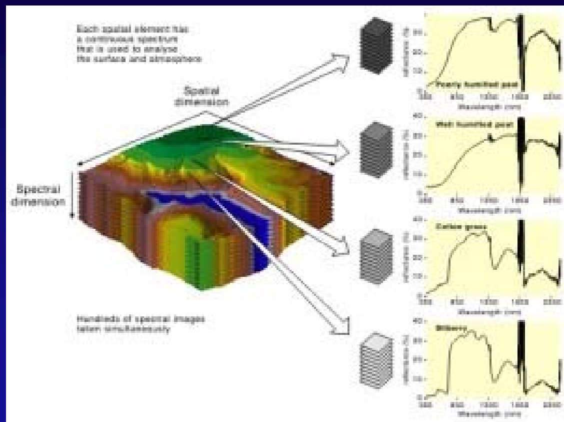


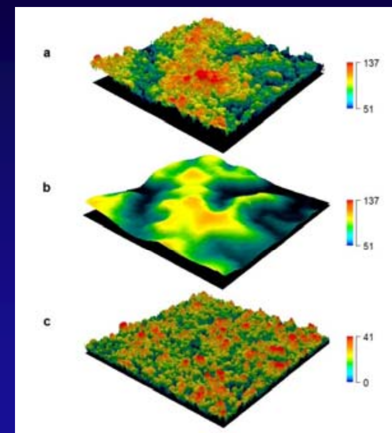
Note: see chapter 21, Ramsey et al.



Hyperspectral Data on Tropical Forests

Advances in Combining Hyperspectral and LIDAR over Tropical Forests





Hyperspectral for
canopy
biochemistry

LIDAR for
canopy structure including
height,
crown shape,
leaf area,
biomass, and
basal area

Hyperspectral + LIDAR for
characterize parameters such as
biochemistry
height
canopy cover
leaf area
canopy chlorophyll content, and
canopy water content

Note: see chapter 20, Thomas et al.

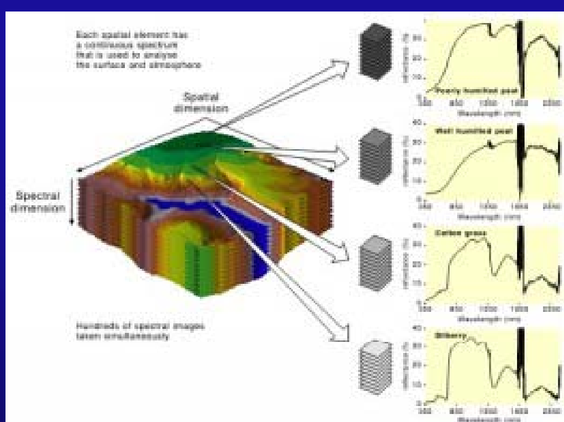
Hyperspectral Data on Tropical Forests

Advances in Combining Hyperspectral and Lidar over Tropical Forests

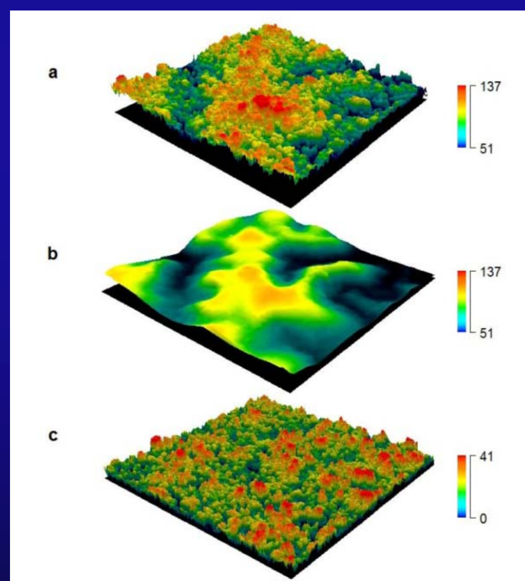
High-fidelity hyperspectral data can detect detailed biochemical information, while lidar peers deeper into the canopy and helps in analyzing the hyperspectral data by interpreting its structural signal and isolating information rich content.

Commercial hyperspectral and lidar sensors are already being combined for joint flights, and improvements in performance and capabilities are also advancing rapidly.

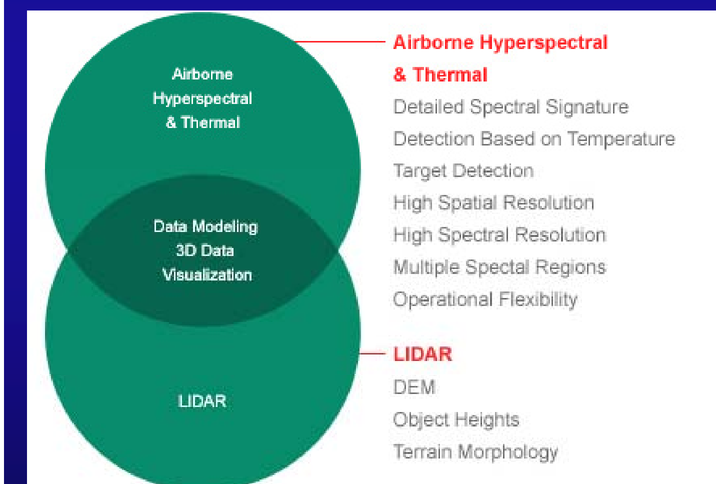
These types of sensors need to fly over more sites where detailed field data can be collected, and just as important, these datasets need to reach a broader research community to be fully exploited.



Hyperspectral tree signatures

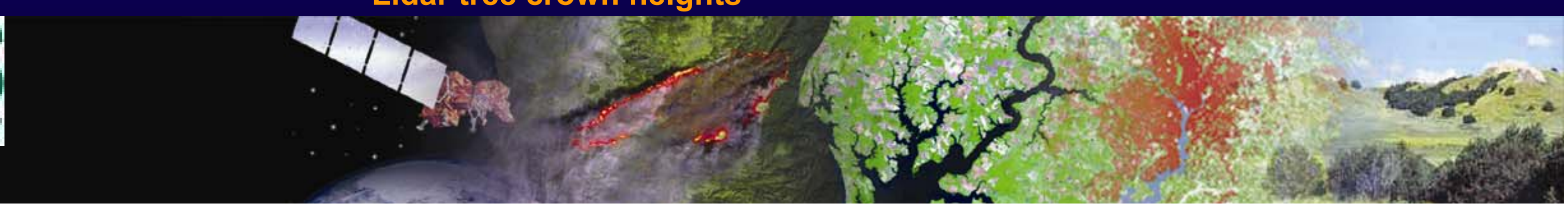


Lidar tree crown heights



Hyperspectral & thermal + Lidar

Note: see chapter 18, Clark et al.



Hughes Phenomenon

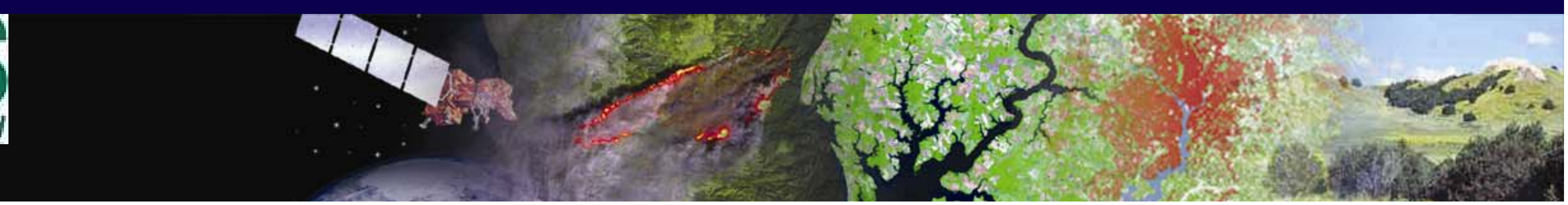
(or Curse of High Dimensionality of Data) and

overcoming data redundancy through Data Mining

Hyperspectral Data (Imaging Spectroscopy data)
Not a Panacea!

For example, hyperspectral systems collect large volumes of data in a short time. Issues include:

- data storage volume;
- data storage rate;
- downlink or transmission bandwidth;
- computing bottle neck in data analysis; and
- new algorithms for data utilization (e.g., atmospheric correction more complicated).



Hyperspectral Data (Imaging Spectroscopy data)

3 Major Issues in Dealing with Hyperspectral Data

1. **Data Dimensionality:** As a result of high data dimensionality (e.g., imagine a hyperspectral data cube with 100s of bands of data) storage and processing of large datasets, especially when we study large areas, will be an issue;
2. **Data Redundancy:** often the adjacent bands provide same information, so for any given application we will have numerous bands that are redundant; and
3. **Hughes Phenomenon:** As the number of bands in an image increases, the number of observations required to train a classifier increases exponentially to maintain the classification accuracies.

Note: see chapter 4, Bajwa et al.

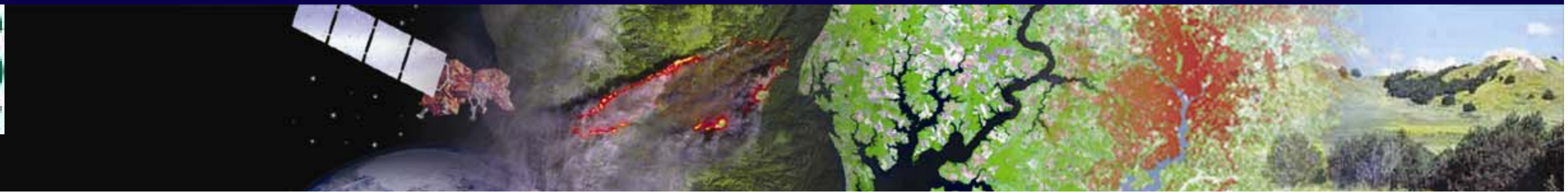
Definition of Hughes Phenomenon

Hughes Phenomenon

As the number of bands in an image increases, the number of observations required to train a classifier increases exponentially to maintain the classification accuracies. This is called Hughes phenomenon, which refers to the loss of classifiability of an image with the same fixed number of training samples when the dimensionality of data increases. Often, it is not possible to increase the size of training data due to time and budgetary constraints. In such cases, the data dimensionality must be reduced using an appropriate feature selection method.

Due to the small number of training samples and the high number of features available in remote sensing applications, reliable estimation of statistical class parameters is a challenging goal. As a result, with a limited training set, classification accuracy (in full-pixel sense) tends to decrease as the number of features increases. This is known as the Hughes effect.

Note: see chapter 4, Bajwa et al., chapter 5, Plaza et al.



Hughes Phenomenon and Overcoming the Same in Vegetation Studies

Data Mining Methods and Approaches

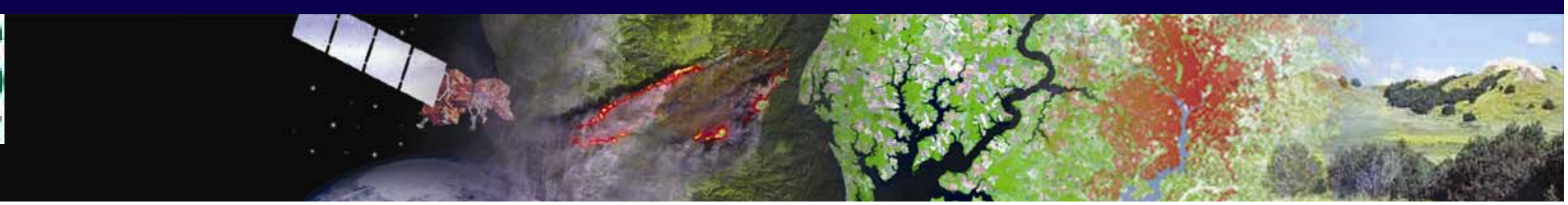
(a) Highlight data redundancy or Hughes phenomenon in hyperspectral narrowband data,

(b) Present methods and approaches of feature selection and information extraction,

(c) Demonstrate ways and means of overcoming the Hughes phenomenon, and

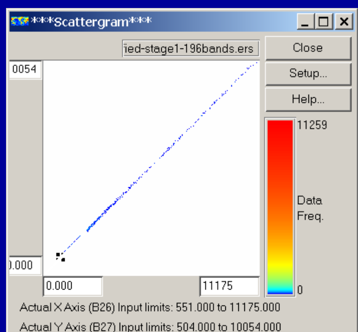
(d) Developing or presenting algorithms to attain high accuracies in hyperspectral narrowband data classification.

Note: chapter s 4 and 5 deal with overcoming Hughes Phenomenon. Example in chapter 5: Firstly, supervised SVM classification was used with only 1% training pixels per class to attain accuracies as high as 90% percent. Second, unsupervised linear and non-linear unmixing algorithms were used to determine fractional abundances within a pixel with high accuracies. (chapter 5)



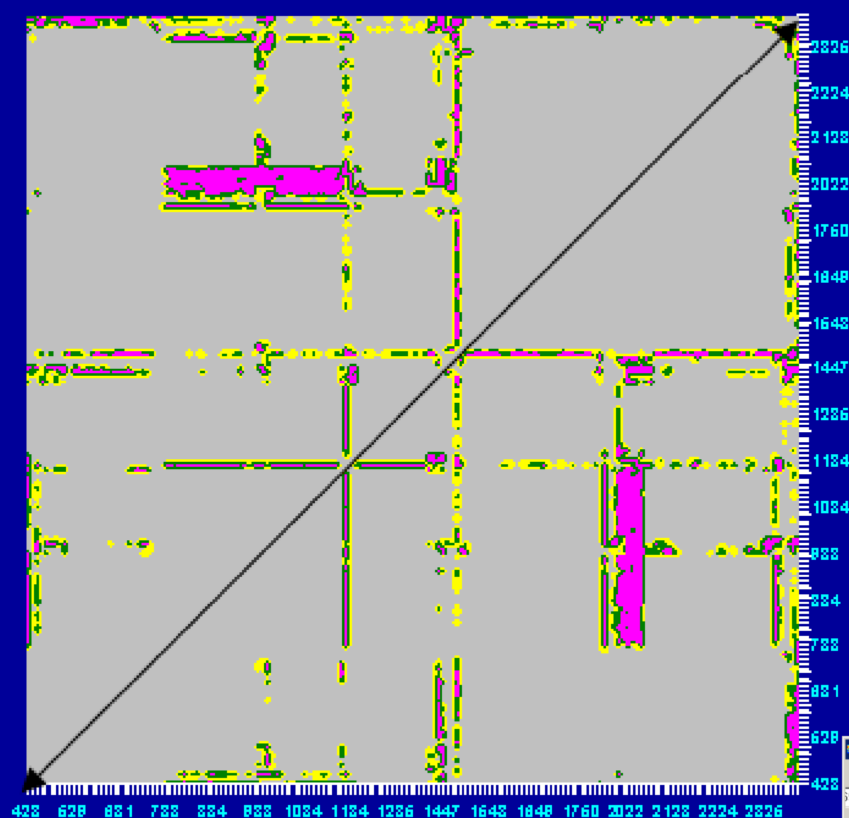
Data Mining Methods and Approaches in Vegetation Studies

Lambda by Lambda R-square Contour Plots: Identifying Least Redundant Bands



Highly redundant: bands centered at 680 nm and 690 nm

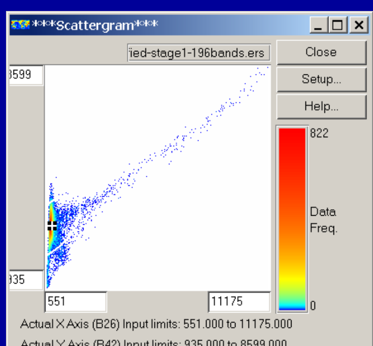
Hyperion rainforest vegetation: Least redundant bands



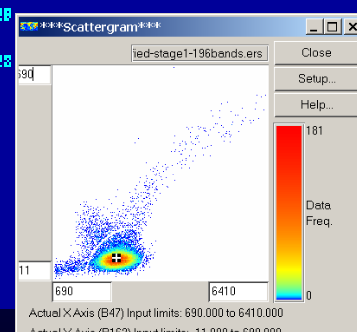
Lambda vs. Lambda Correlation plot for African rainforest Vegetation

R^2 values between wavebands (lesser the R^2 value lesser the redundancy)

- 0.009-0.01
- 0.008-0.009
- 0.007-0.008
- 0.006-0.007
- 0.005-0.006
- 0.004-0.005
- 0.003-0.004
- 0.002-0.003
- 0.001-0.002
- 0-0.001



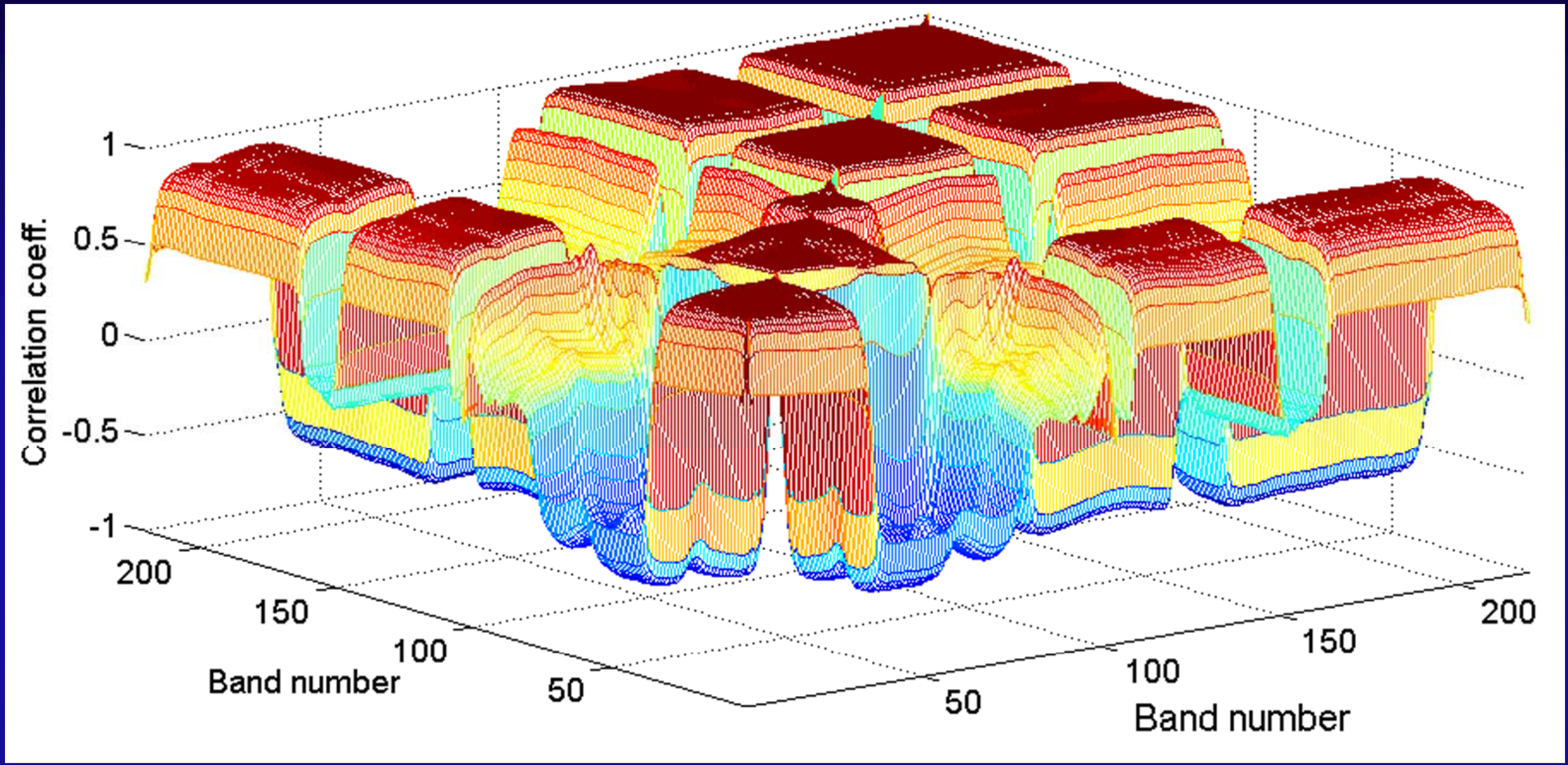
Significantly different: bands centered at 680 nm and 890 nm



Distinctly different: bands centered at 920 nm and 2050 nm

Data Mining Methods and Approaches in Vegetation Studies

Correlation between Bands and Elimination of Redundant Bands



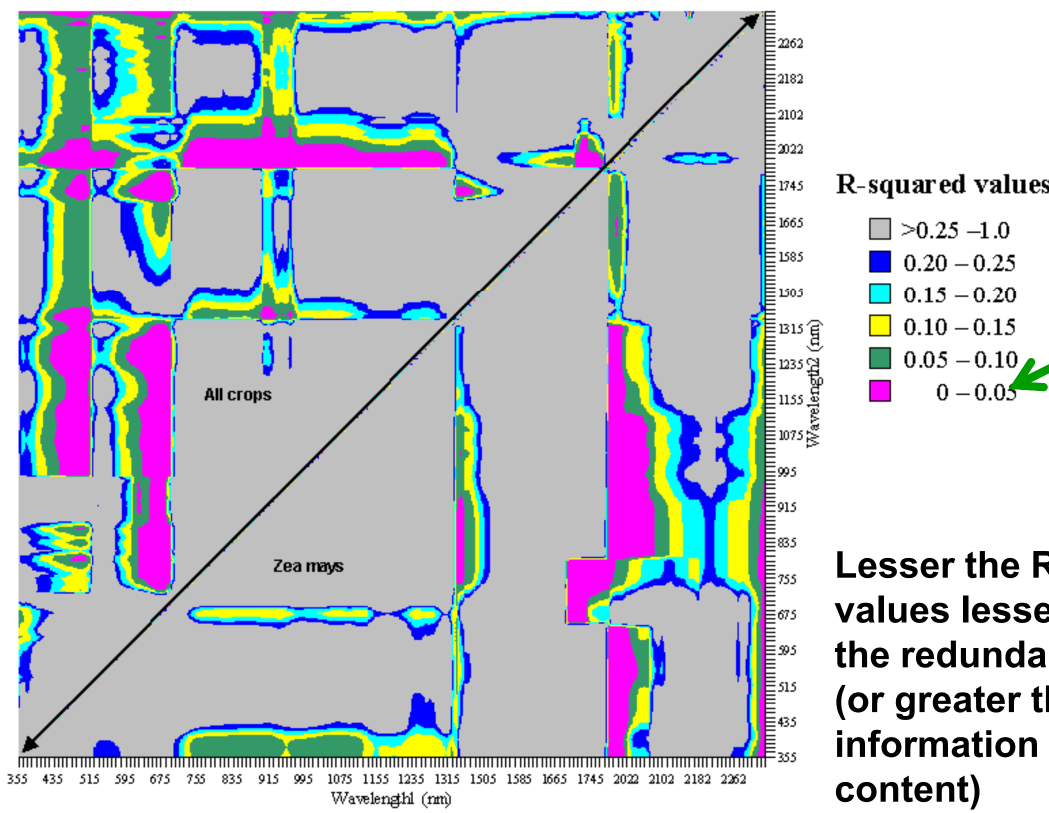
Correlation between the bands of hyperspectral image. The correlation coefficient can vary from −1 to +1. A correlation coefficient of 0 indicates no linear dependency whereas a +1 or −1 indicates a 100% dependency. For a pair of features that are highly correlated, one can be eliminated without losing any information.

Note: see chapter 4, Bajwa et al.

Data Mining Methods and Approaches in Vegetation Studies

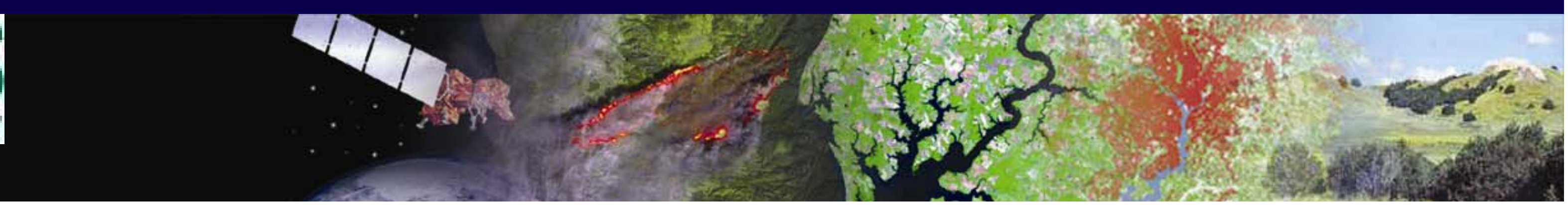
Lambda by Lambda R-square Contour Plots: Identifying Least Redundant Bands

Contour plot of R-squared values of narrowbands for six crop species and *Zea mays* in the west-central African savannas



Lesser the R^2 values lesser the redundancy (or greater the information content)

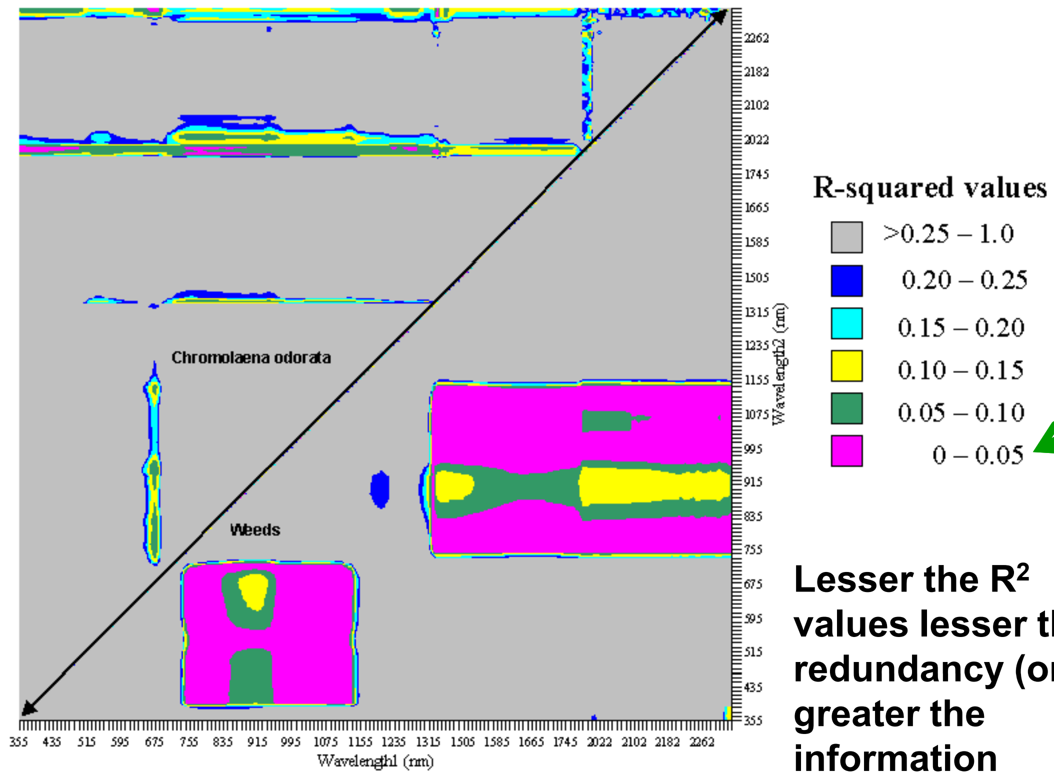
Spectral Region of least Redundancy ……or…….. spectral region of maximum unique information



Data Mining Methods and Approaches in Vegetation Studies

Lambda by Lambda R-square Contour Plots: Identifying Least Redundant Bands

Contour plot of R-squared values of narrowbands for 5 weed species and *Chromolaena odorata* in the west-central African savannas



Lesser the R^2 values lesser the redundancy (or greater the information content)

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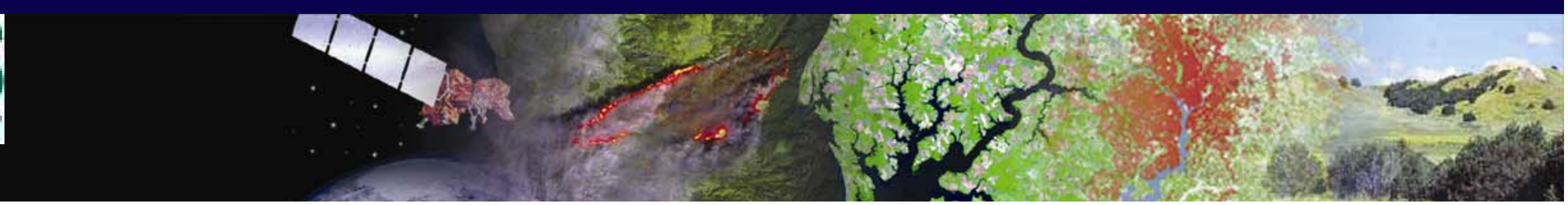


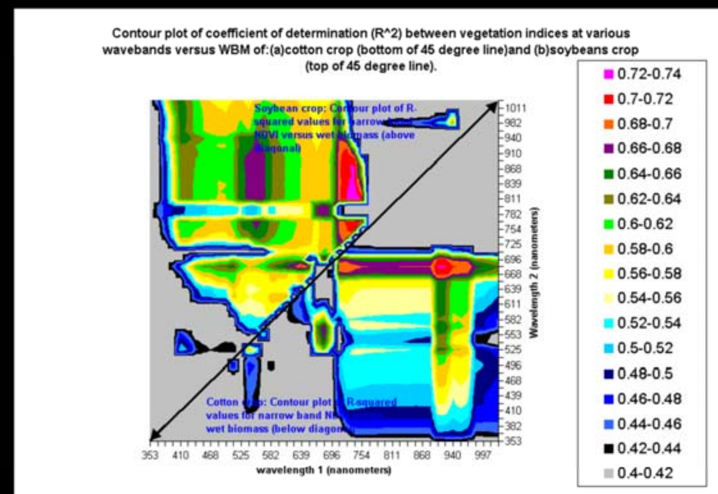
Data Mining Methods and Approaches in Vegetation Studies

Lambda by Lambda R-square Contour Plots: Identifying Most useful Bands

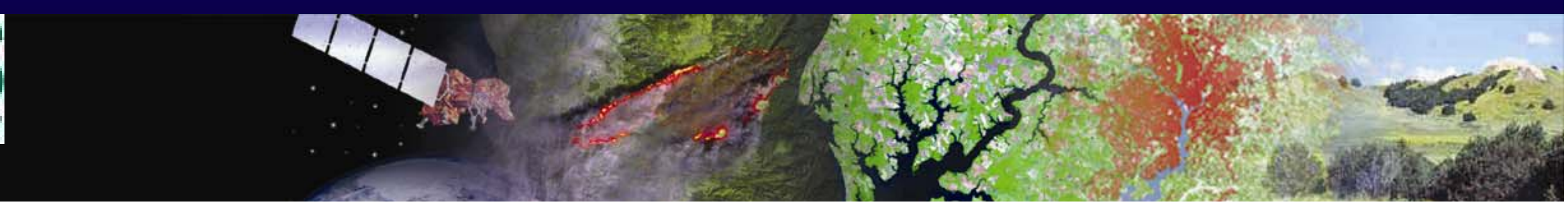
Lambda 1 (λ_1: 400-2500 nm) vs. Lambda 2 (λ_2: 400-2500 nm) plots to determine redundant bands versus most useful bands to study various crop characteristics such as biomass, LAI, yield, chlorophyll, carotenoid, and nitrogen.

These Lambda vs. Lambda plots are **contour plots of R-squared values plotted along the 400 to 2500 nm spectral range (λ_1: 400-2500 nm vs. λ_2: 400-2500 nm)** with an R-squared value for every narrowband combination (e.g., 1 nm band width in many spectroradiometers and 10 nm in Hyperion).

The **"bulls eye" regions of the Lambda vs. Lambda plots are the most useful bands** to study a particular vegetation characteristic. Such Lambda by Lambda plots are also presented in Chapters 8, 11, and 18- reflecting its wide applicability to identify redundant bands and to select the best bands to study various vegetation characteristics.



Note: see chapter 1, 8, 11, and 18



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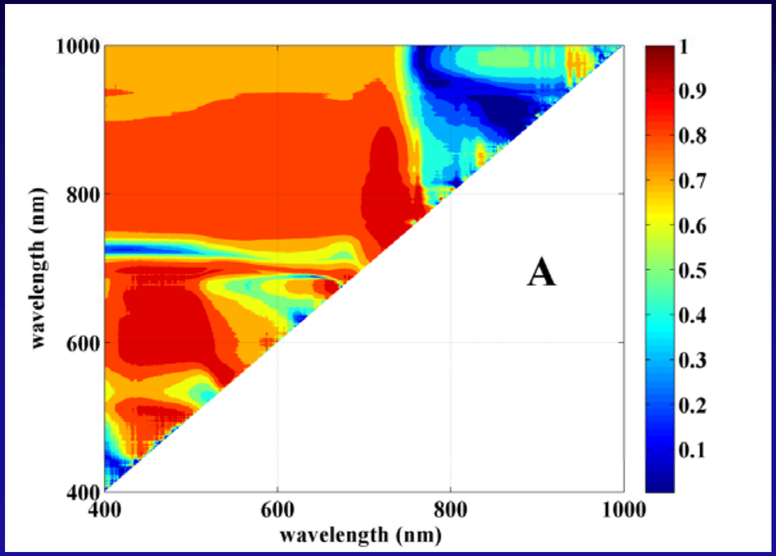
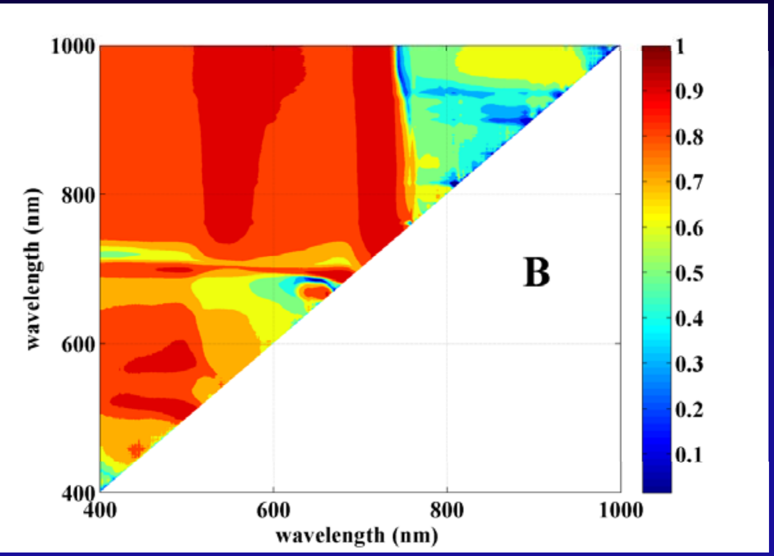
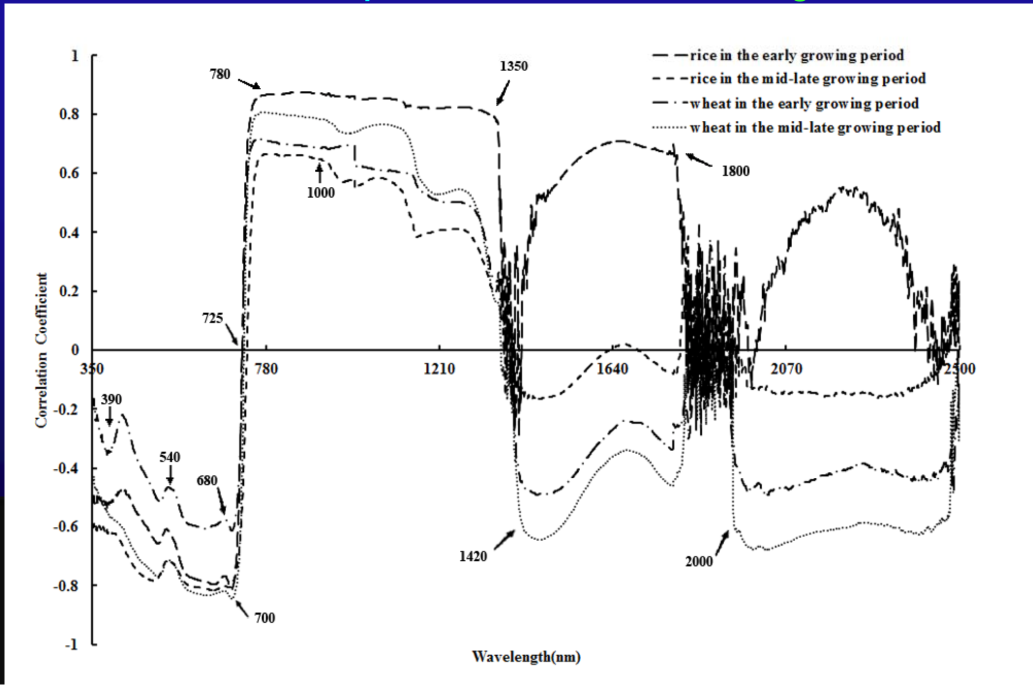
Data Mining Methods and Approaches in Vegetation Studies

Lambda by Lambda R-square Contour Plots: Identifying Most useful Bands





Contour maps of relative R^2-values for linear relationships between SAVI and leaf nitrogen content for rice (A) and wheat (B).



Note: see chapter 8

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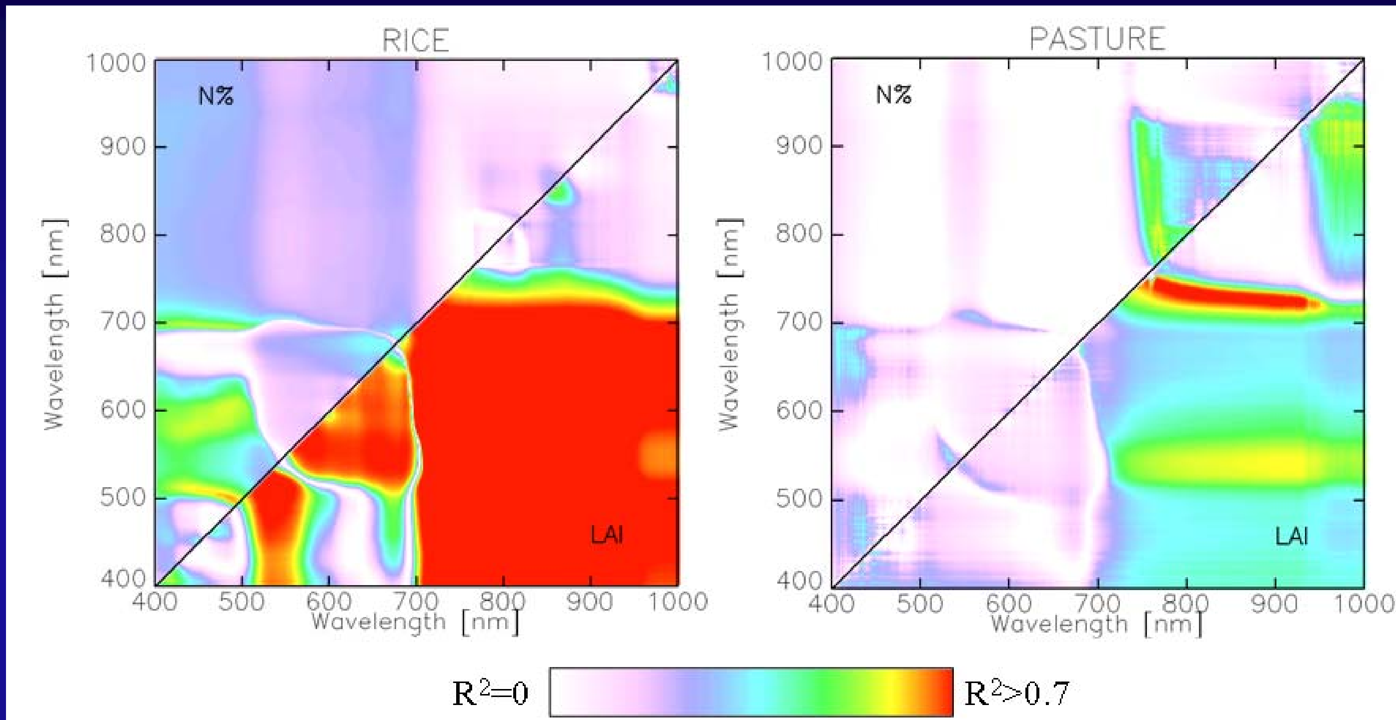
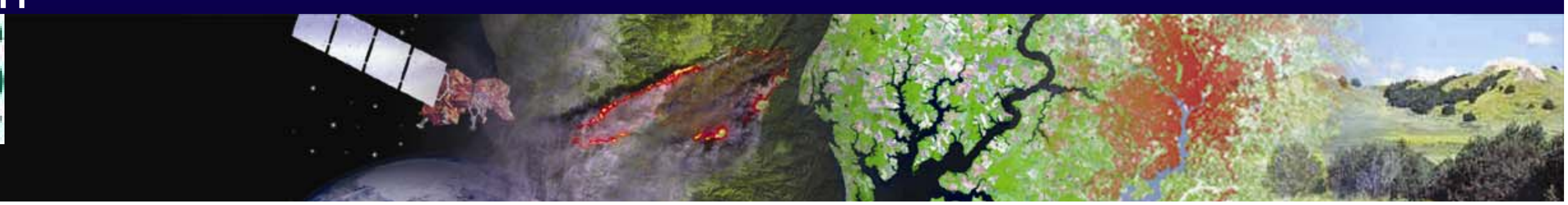
Data Mining Methods and Approaches in Vegetation Studies

Lambda by Lambda R-square Contour Plots: Identifying Most useful Bands



Linear correlation (R^2) between N concentration/LAI and ND for rice (left, [20]) and SR for pasture (right, [21]) for field canopy spectra acquired with a FieldSpec FR PRO spectroradiometer.

Note: see chapter 11



Data Mining Methods and Approaches in Vegetation Studies
Feature selection\extraction and Information Extraction

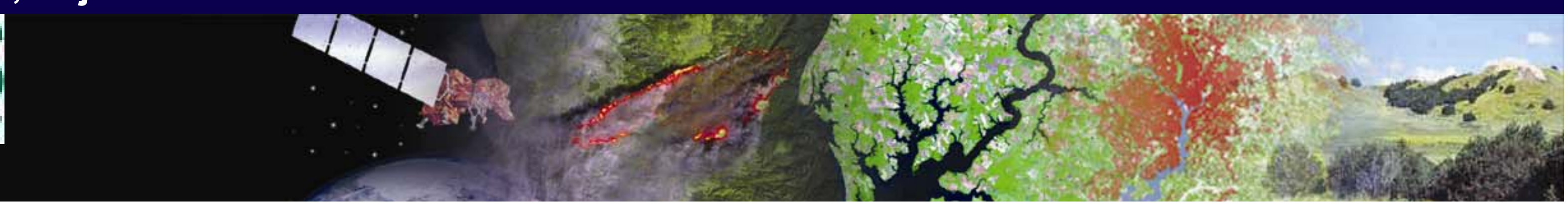
Feature selection is necessary in any data mining effort. Feature selection reduces the dimensionality of data by selecting only a subset of measured features (predictor variables). Feature selection methods recommendation based on:

(a) Information Content (e.g., Selection based on Theoretical Knowledge- what bands are important for what?, Information Entropy),

(b) Projection-Based methods (e.g., Principal Component Analysis or PCA, Independent Component Analysis or ICA),

(c) Similarity Measures (e.g., Correlation coefficient, Spectral Derivative Analysis), and

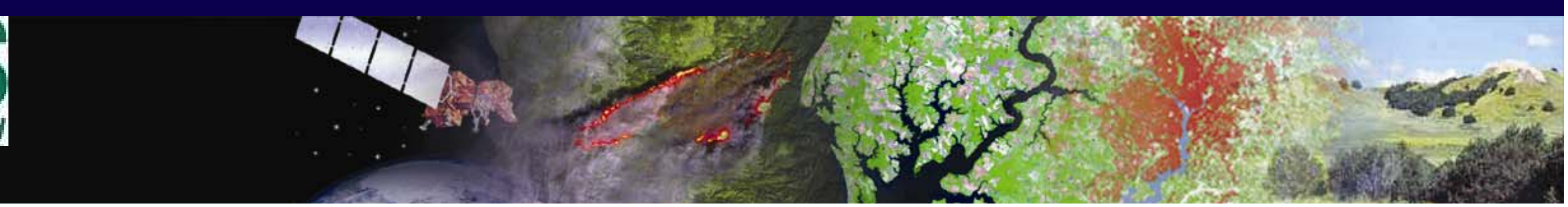
Note: see chapter 4, Bajwa et al.



Data Mining Methods and Approaches in Vegetation Studies
Principal Component Analysis: Identifying Most useful Bands

3. **Principal component analysis (PCA) and PCA derived indices [PRINCOMP algorithm of SAS (SAS, 1999); also MAXR algorithm of SAS]. discrimination indicators are:**

- **Percent variability explained by various principal components**
- **R^2 values between indices derived using data from principal component bands 1 and 2 versus crop variables**



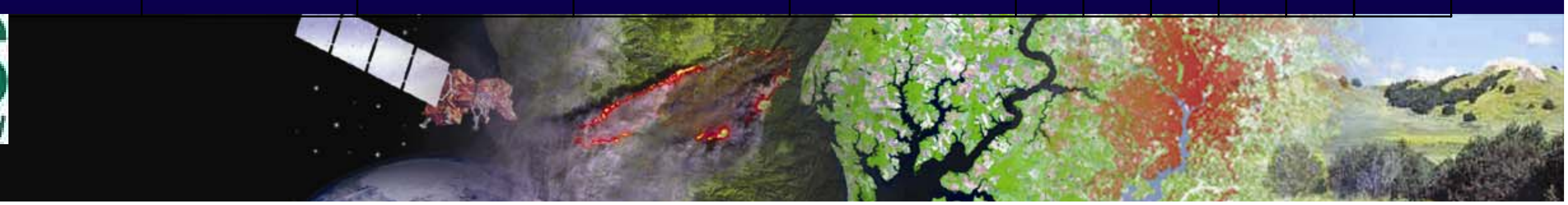
Data Mining Methods and Approaches in Vegetation Studies

Principal Component Analysis: Identifying Most useful Bands

Wavebands with Highest Factor Loadings

Principal component analysis for crop species

Crops	Band centers (nm) with first 20 highest factor loadings					% variability explained					
	PCA1	PCA2	PCA3	PCA4	PCA5	PCA 1	PCA 2	PCA 3	PCA 4	PCA 5	5 cumulative PCAs
Cassava	1725;1715;1705;1575; 1695;1605;1735;1585; 1555;1595;1565;1685; 1625;1655;1545;1615; 1665;1635;1675;1645	635;625;695;615;645; 605;595;655;585;705; 575;685;665;515;525; 565;535;555;545;715	2002;2342;2322;2282; 2312;2312;2272;1455; 1380;2012;2332;2022; 2222;2292;2262;1465; 1982;2252;1445;2132	2002;1245;1255;1235; 1275;1265;1285;1992; 2042;2032;2262;2062; 2292;1225;2322;1982; 2072;2232;2012;2282	2332;2342;2322;1982; 2312;2312;1445;2292; 2022;1992;2262;865; 875;855;775;885;785; 845;795;805	63.9	18.9	5.6	2.6	1.9	92.7
Dominating bands	EMIR	Green; Red	MIR; MMIR; FMI	R;EMIR;MMIR;FN	; EMIR; MMIR; FMIR						
Corn	1675;1665; 1645;1655; 1685;1695;1635;1705; 1625;1715;1725;1615; 1735;1605;1745;1595; 1755;1585;1765;1575	2032;2052;2042;2082; 2072;2062;2092;2102; 1982;2112;1465;2122; 2022;1455;2132;1992; 1475;2142;1485;2252	2002;2012;2342;1992; 2022;1982;2332;2322; 2032;2072;1255;1245; 2042;1275;1285;1265; 2062;1235;2052;1380	355;365;375;385;395; 405;415;425;435;1445; 1245;445;1255;1235; 1275;1265;1285;1225; 1135;1455	2342;2002;2012;1992; 1982;2332;2022;355; 375;2052;365;2322; 385;395;405;2042; 2062; 2312;2312;415	67.0	16.1	7.8	2.2	1.9	94.9
Dominating bands	EMIR	MIR; MMIR; FMI	FNIR; EMIR; MMIR; FMIR	UV; Blue; FNIR; EMIR	UV; Blue; EMIR; MMIR; FMIR						

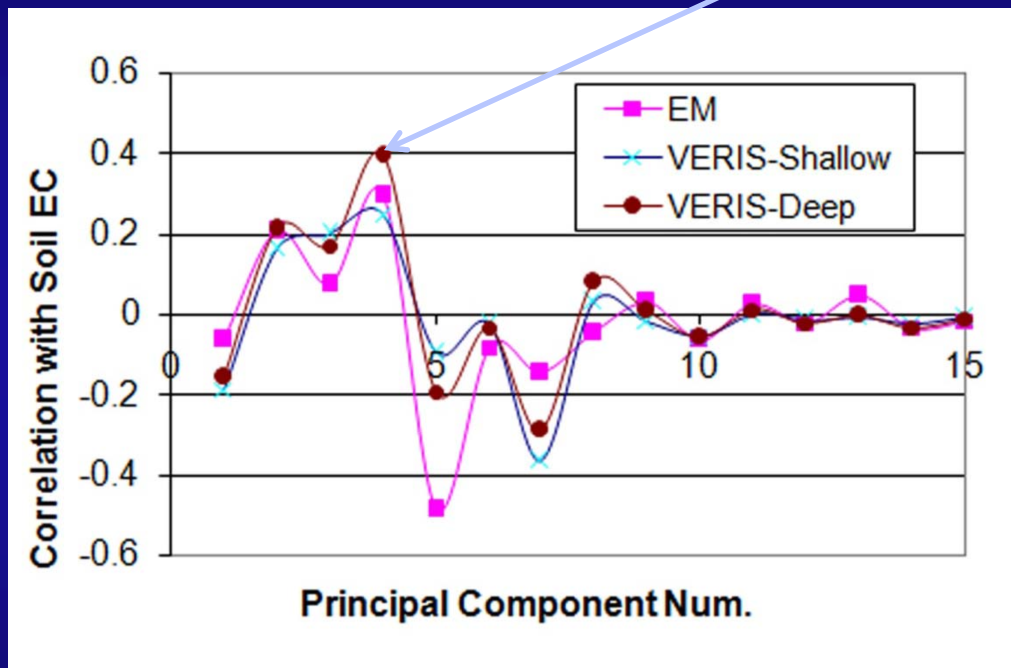


Data Mining Methods and Approaches in Vegetation Studies

Principal Component Analysis: Limitations

Here, hyperspectral image with 120 bands in the visible and NIR region explained 99.6% of variability in first 3 PCA's. However, soil electrical conductivity showed the highest cross-correlation with PC5 and PC4 which showed only 0.2% and 0.1% of variability in the image, respectively.

PCA is also not ideal for detecting small classes that are represented by relatively fewer pixels.



Correlation between principal components of a hyperspectral image of an agricultural field and apparent soil electrical conductivity at two different depths.

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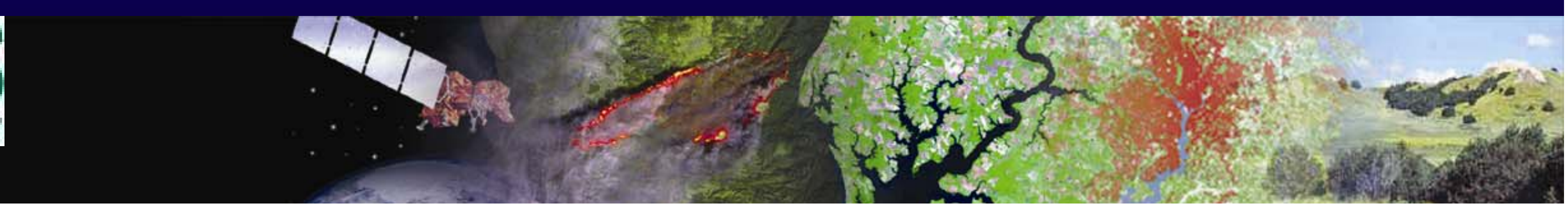

Data Mining Methods and Approaches in Vegetation Studies

Feature selection\extraction and Information Extraction

Numerous Data Mining Approaches for Various Applications to overcome Hughes Phenomenon

A summary of research showing of numerous applications of data mining (feature selection/extraction and information extraction) techniques applied to hyperspectral remote sensing.

Reference	Application	Feature selection method	Information extraction methods
48	biomass		Simple or multivariate regression, PLSR
49	Forest productivity (wood production, canopy N) - AVIRIS		PLSR
77	Land cover classification – OMIS data	PCA	ANN
81	Land cover classification – DAIS data	SVM, MNF	SVM, SVM-GA
60	Land cover classification – AVIRIS data92AV3C	LDA, SVM, Regularized RBFNN(R-RBFNN), kernel based Fisher's discrimination (k-FD). Regularized AdaBoost (R-Adaboost)	
89	Crop type detection - HyMap	R-RBFNN, SVM-RBF kernel, R-AdaBoost	
91	Forest pigment (Chl-a) concentration & LAI -CASI	Cross-correlation	simple linear regression
92	Forest understory information (canopy structure & pigments) – DAIS & ROSIS		MLP NN model
93	Forest LAI, forest species distribution – DAIS, ROSIS, MIVIS	Cross-correlation	Regression model for LAI, SAM for species distribution
94	Postfire vegetation recovery - Hyperion	Cross-correlation, PCA, stepwise discriminant analysis	Object oriented nearest-neighbor fuzzy classification
95	Crop coverage-ImpSensor V10	ICA	ICA
96	Forest Canopy N, LAI - AVIRIS & Hyperion	Derivative analysis	PLSR
97	Forest canopy LAI - Hyperion	Cross-correlation	Simple linear regression
98	Invasive species mapping-HyMap	MNF, continuum removal	SMA, SAM
99	Canopy water content & LAI-AVIRIS & MODIS	Knowledge-based band selection	RTM and simple regression
100	Vegetation classification-HyMap & CASI	Transformed divergence, SBS & band width increase	MLC

1

Note: see chapter 4, Bajwa et al.

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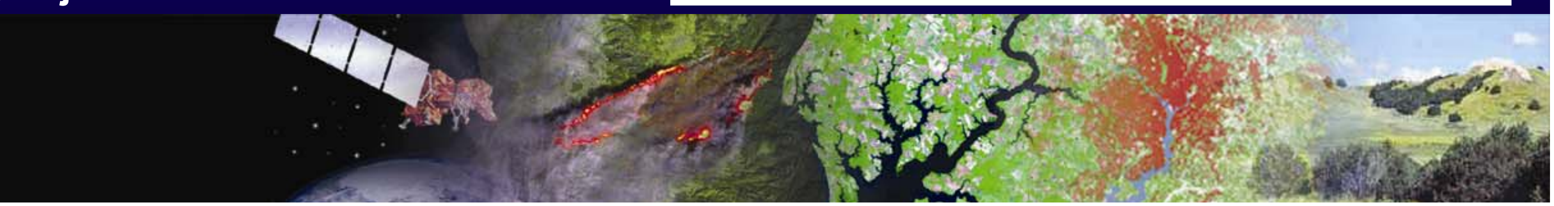


Hyperspectral Data (Imaging Spectroscopy data)

Data Mining: Which Methods to Use?

With the proper selection of a suite of data mining techniques, it is possible to”

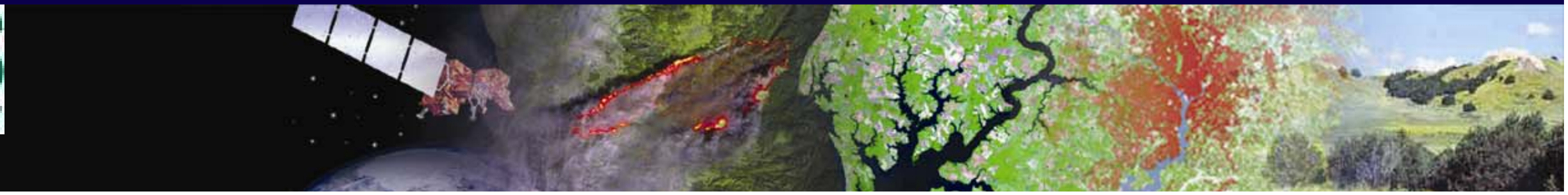
- **Reduce data dimensionality**
- **Reduce data redundancy, and**
- **Extract unique information**

from hyperspectral images that are, often, substantial improvement when compared with multispectral image data.

One may choose a specific combination of feature selection/extraction and information extraction methods depending on the:

- **application and objectives,**
- **the scale of the problem,**
- **skill level available,**
- **availability of training data,**
- **time, and**
- **budget constraints.**

Note: see chapter 4, Bajwa et al.



Hyperspectral Remote Sensing Vegetation

Note to Workshop Participants

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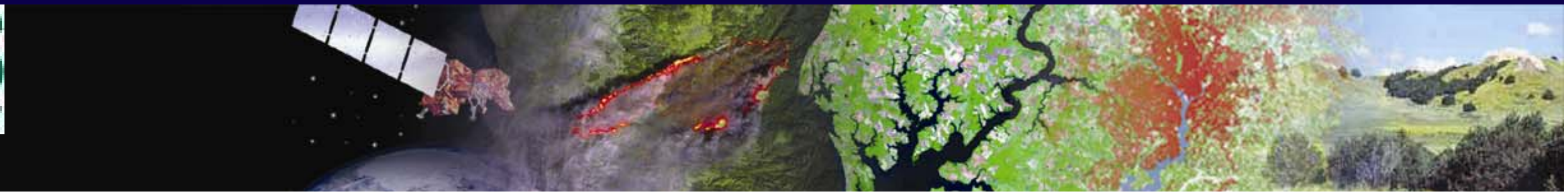
Thenkabail, P.S., Lyon, G.J., and Huete, A. 2011. Book entitled: "Advanced Hyperspectral Remote Sensing of Terrestrial Environment". 28 Chapters. CRC Press- Taylor and Francis group, Boca Raton, London, New York. Pp. 781 (80+ pages in color).



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