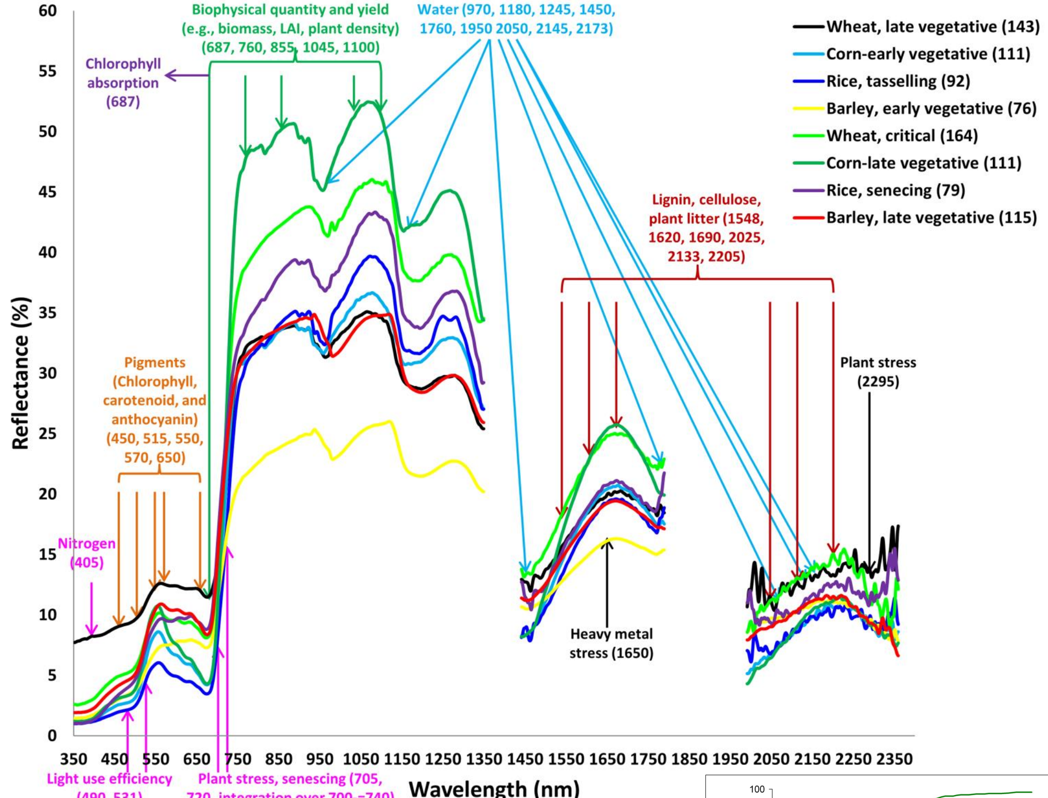
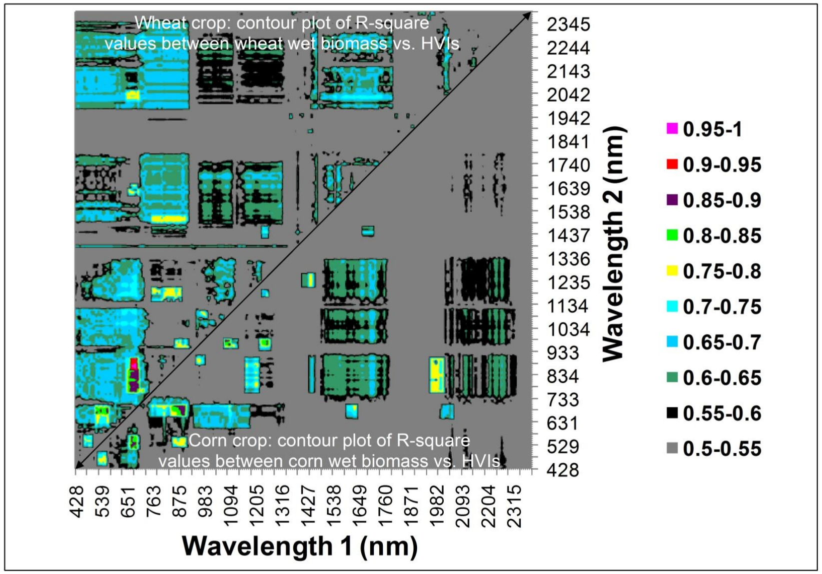
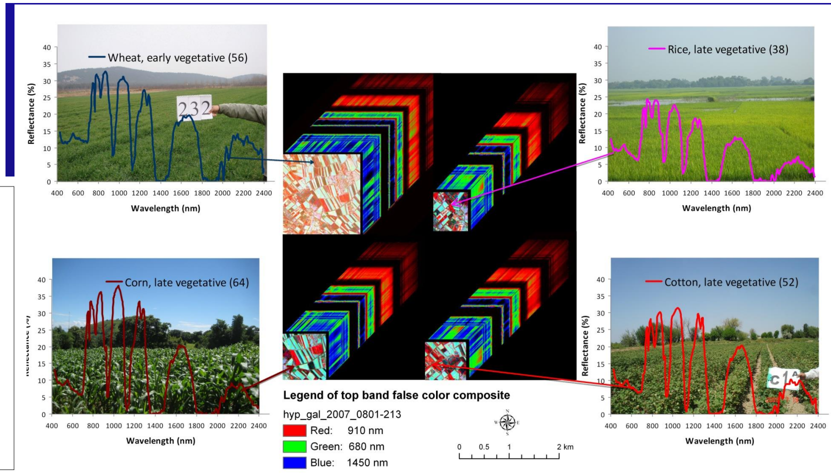
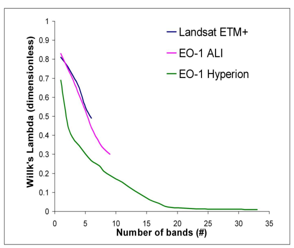
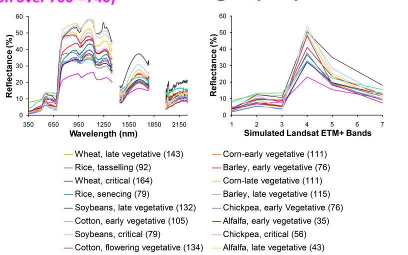
Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation: Some Recent Advances in Data and Methods

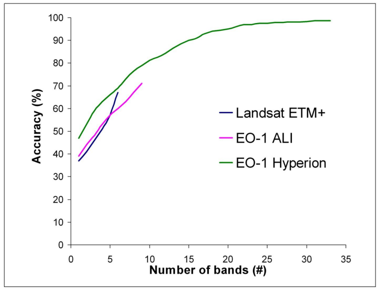












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Prasad S. Thenkabail

Research Geographer, U.S. Geological Survey (USGS)

September 11-12, 2013. Cologne, Germany

Workshop on UAV-based Remote Sensing Methods for Monitoring Vegetation

Importance of

Hyperspectral Sensors in

Study of Vegetation

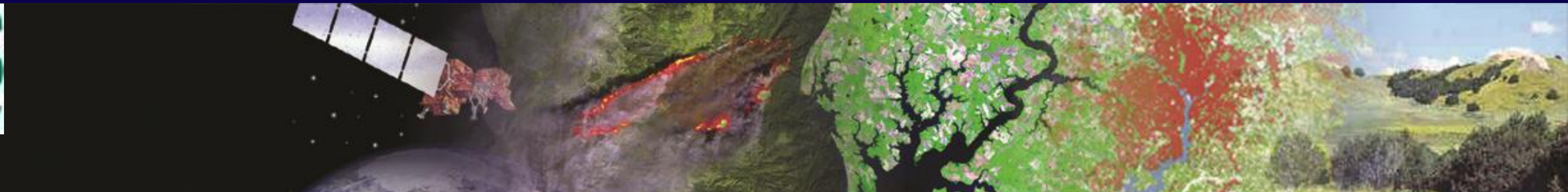
Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation

Importance of Hyperspectral Sensors 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:

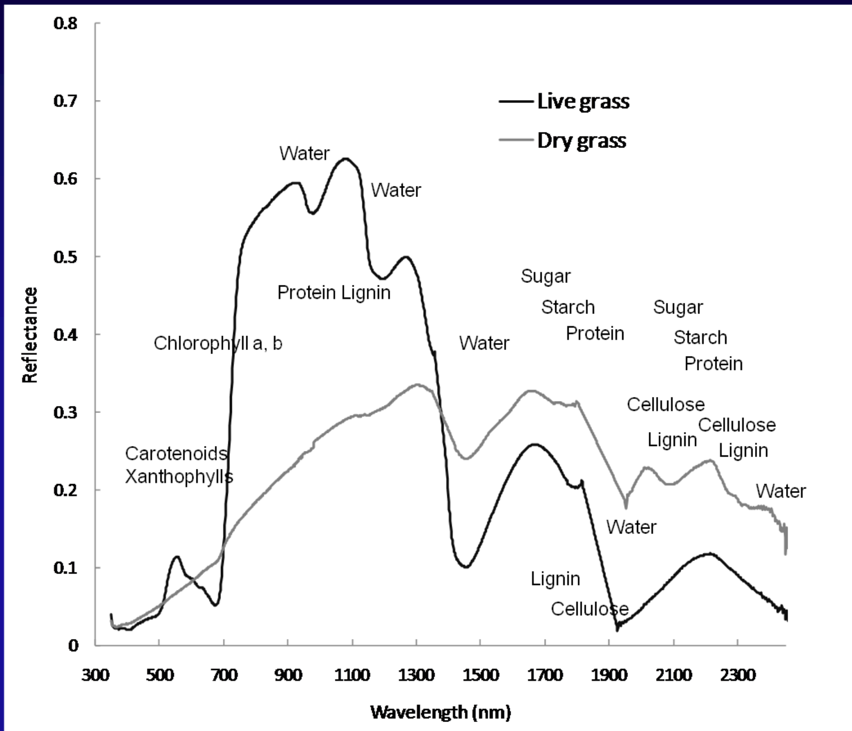
(a)Species composition (e.g., *chromolenea odorata vs. imperata cylindrica*);
(b)Vegetation or crop type (e.g., soybeans vs. corn);
(c)Biophysical properties (e.g., LAI, biomass, yield, density);
(d)Biochemical properties (e.g, Anthrocyanins, Carotenoids, Chlorophyll);
(e)Disease and stress (e.g., insect 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……..

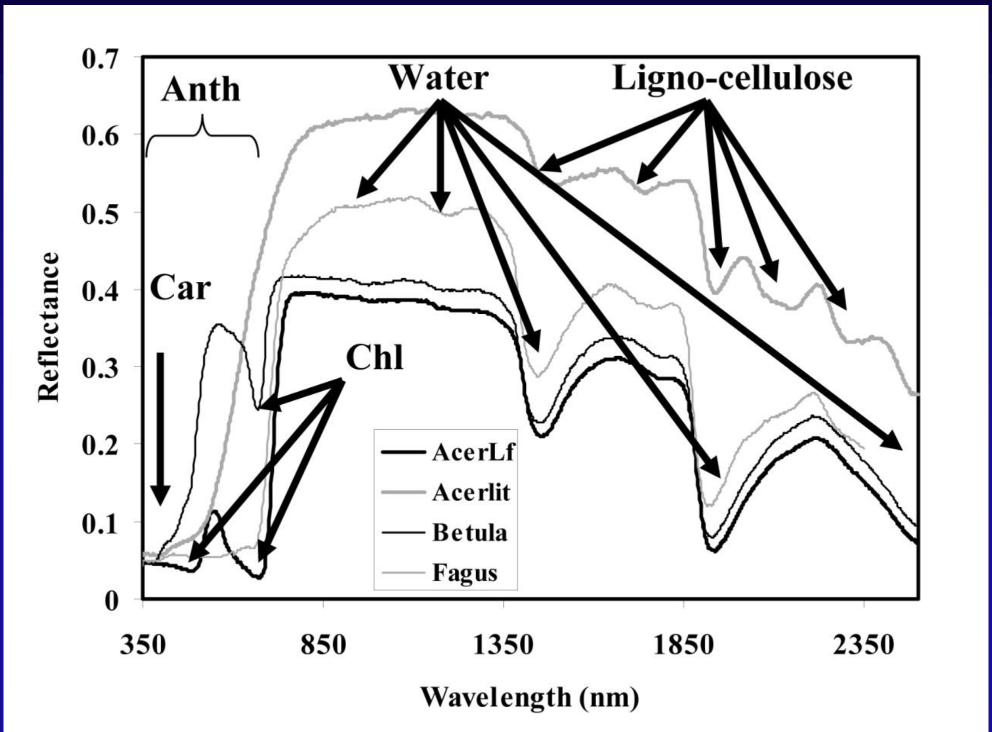


Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation

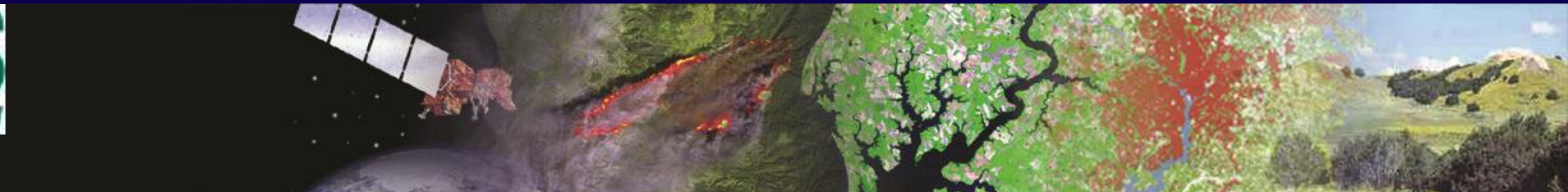
Spectral Wavelengths and their Importance in the Study of Vegetation Biophysical and Biochemical properties



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

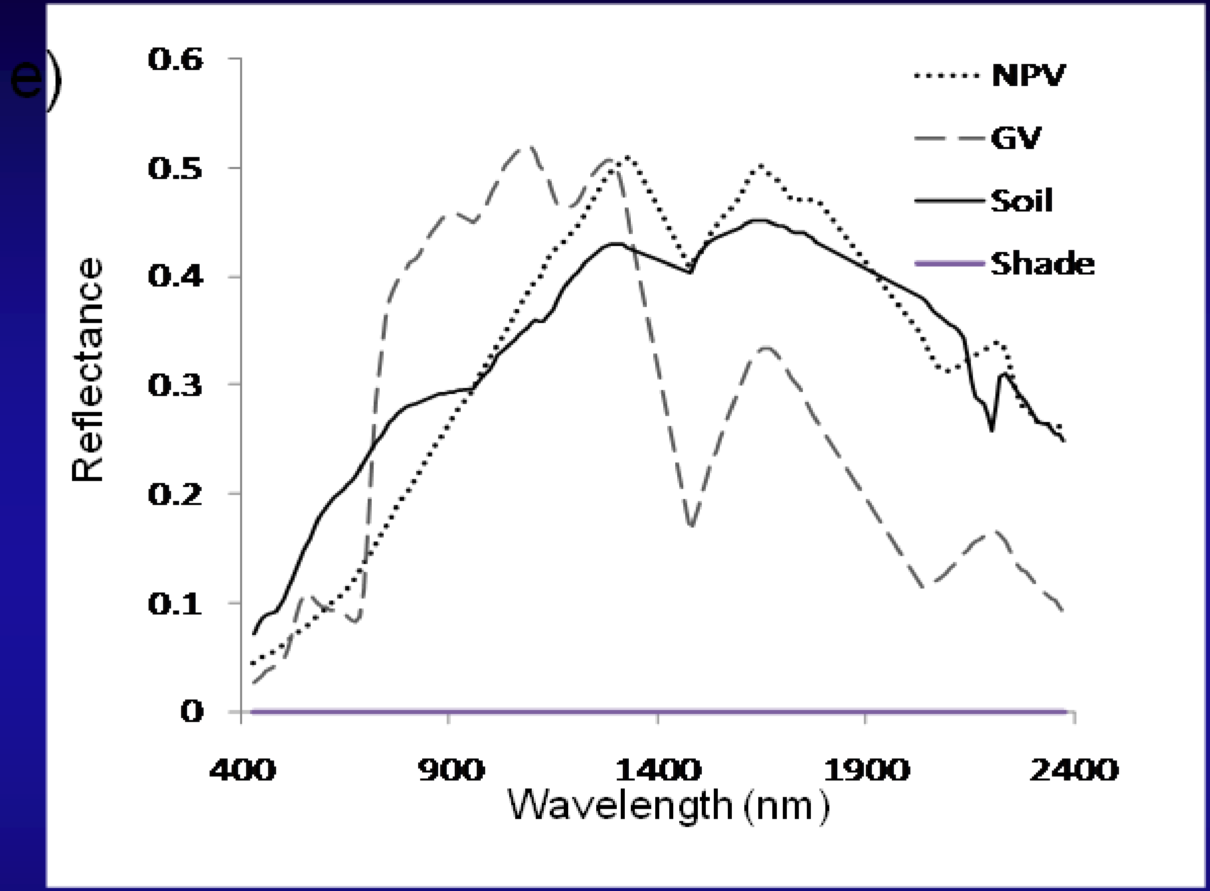


Reflectance spectra of leaves from a senesced birch (Betula), ornamental beech (Fagus) and healthy and fully senesced maple (AcerLf, Acerlit) illustrating Carotenoid (Car), Anthocyanin (Anth), Chlorophyll (Chl), Water and Ligno-cellulose absorptions.



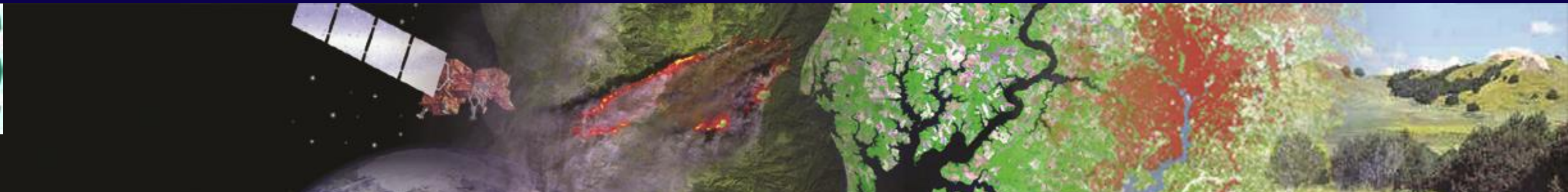
Hyperspectral Remote Sensing of Vegetation

Typical Hyperspectral Signatures of Certain Land Components



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

See chapter 9, Numata et al.



Definition of
Hyperspectral Sensors in
Study of Vegetation

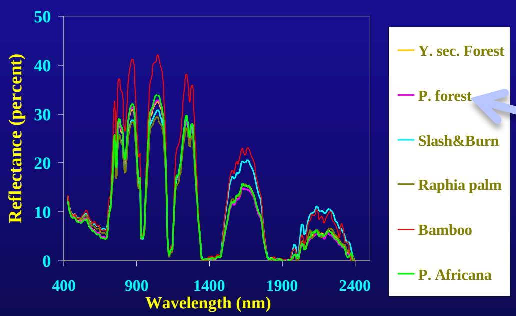
Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation

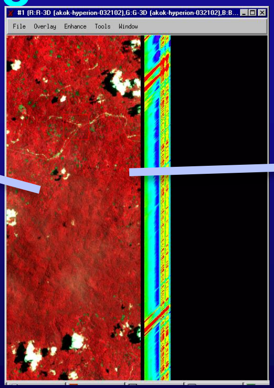
Definition of Hyperspectral Data

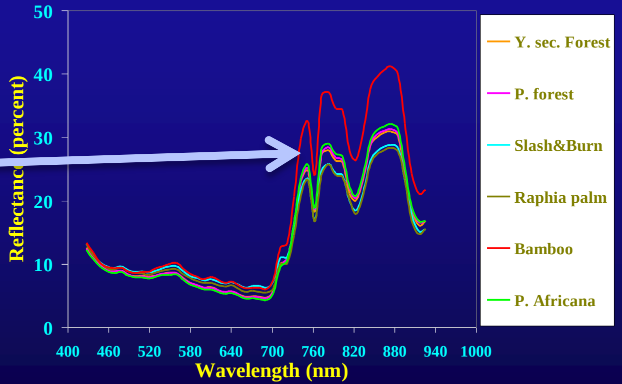
A. consists of **hundreds or thousands of narrow-wavebands** (as narrow as 1; but generally less than 5 nm) along the electromagnetic spectrum;

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.







Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation

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

Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation

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
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

Existing hyperspectral spaceborne missions:
1. Hyperion (USA's NASA),
2. PROBA (Europe's ESA;'s), and

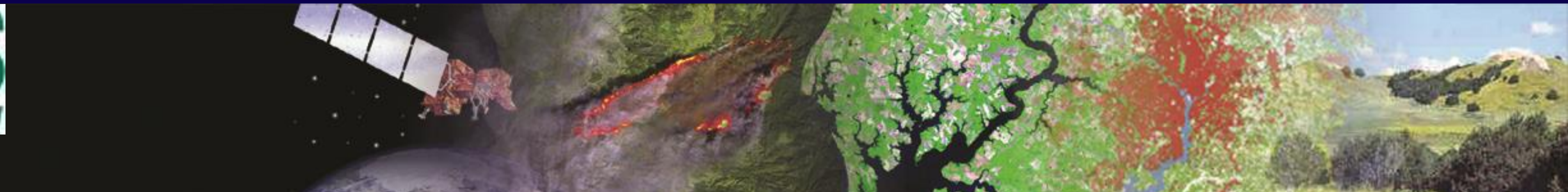
There are some twenty spaceborne hyperspectral sensors

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 m spatial resolution hyperspectral images with a 30 km swath width, which may enable a provision of high temporal resolution, multi-angular hyperspectral observations over the same targets for the hyperspectral BRDF characterization of surface.

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



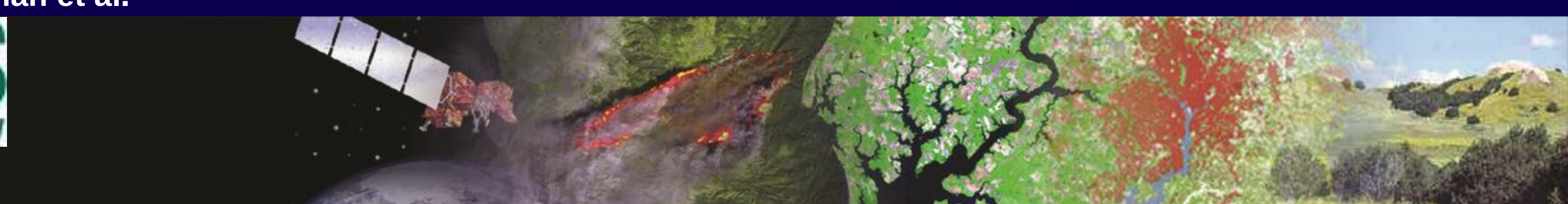
Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation

Earth and Planetary Hyperspectral Remote Sensing Instruments

	Hyperspectral Instrument	Spectral Range (nm)	# of Channels	Spectral Bandpass	Spatial Resolution	Operational Dates
Earth						
	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
Airborne	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.



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 SpaceImaging	1 m (P), 4 m (M)	4	10000, 625
QUICKBIRD Digital Globe	0.61 m (P), 2.44 m (M)	4	16393, 4098
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

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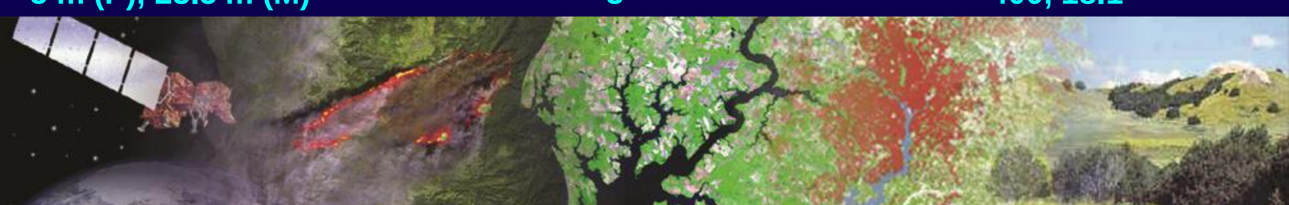
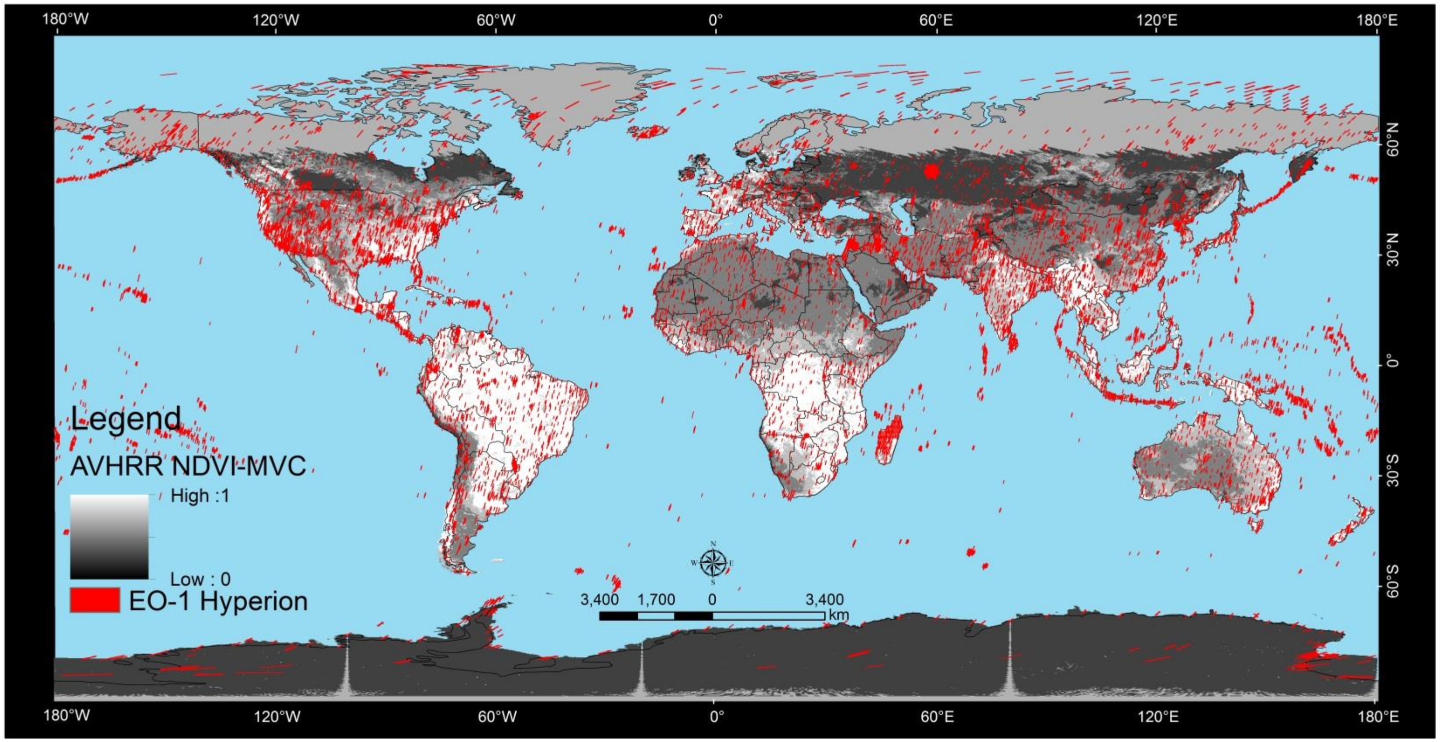


Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation
~64,000 Hyperspectral Hyperion Images of the World (2001-2013)

185 km by 7.5 km; 242 bands, 10 nm wide in 400-2500 nm; 30 m spatial resolution



http://earthexplorer.usgs.gov/; http://eo1.usgs.gov/

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Hyperspectral Data Characteristics

Spectral Wavelengths and their Importance in Vegetation Studies

Hyperspectral Data in Study of Complex Vegetation

e.g., Hyperion EO-1 Data for Biophysical Characteristics of African rainforests


Primary forests


Degraded primary forests


Secondary forests


Musanga regrowth


Ra[illegible]ia palm lowland


Permanently flooded swamp forest


Degraded permanently flooded swamp forest


Forest Fragmentation along roads


Slash-and-burn


Slash-and-burn agriculture

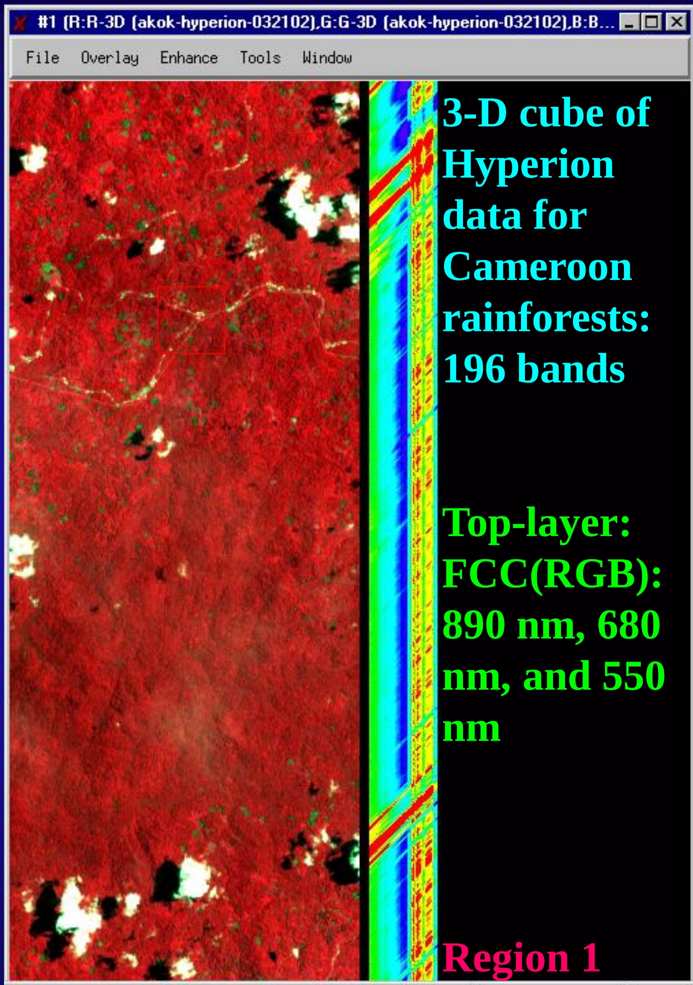

2-yr regrowth; Chromolaena Odorata

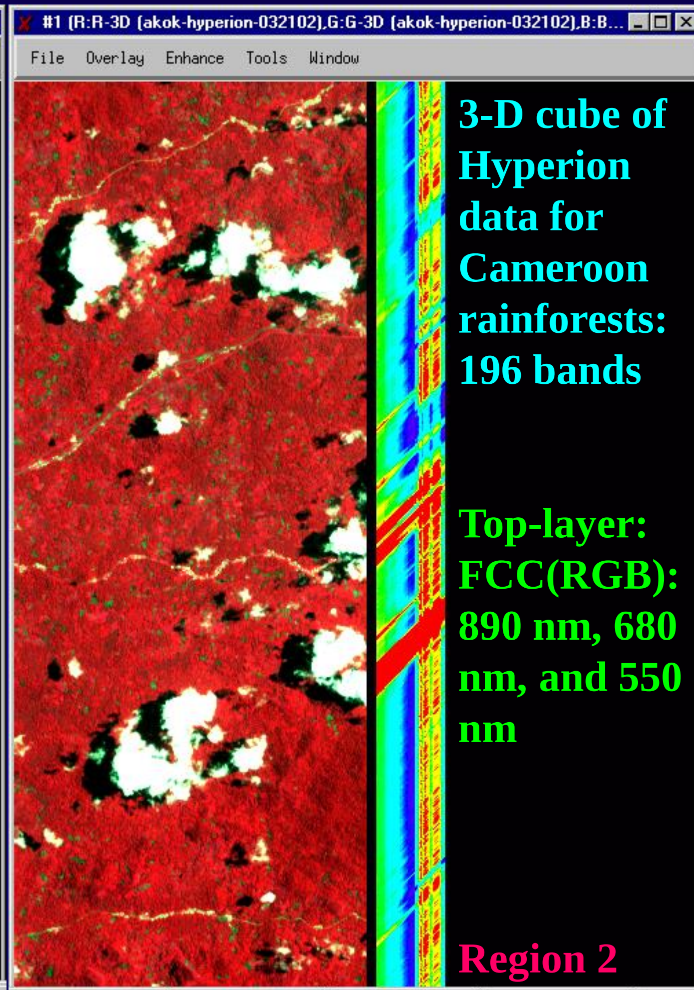

50-yr regrowth

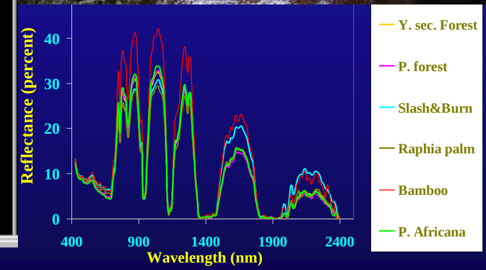

Cocoa plantations

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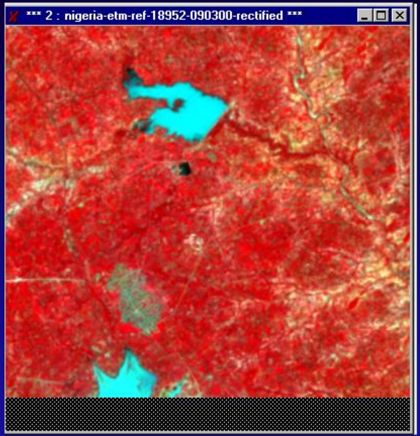
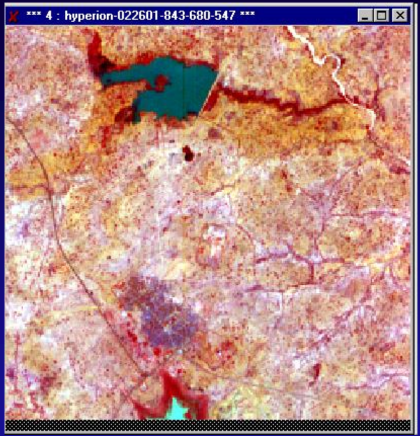
Hyperion Narrow-Band Data from EO-1 Vs. ETM+ Broad-band Data

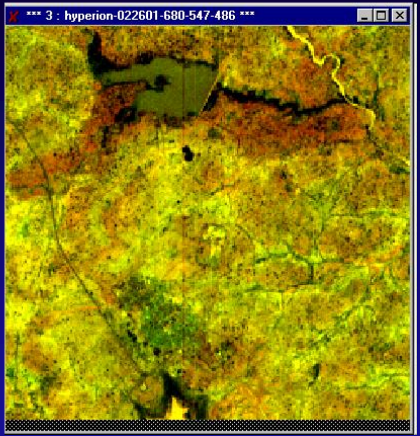
Hyperspectral Data Provides Numerous Ways of Looking at Data



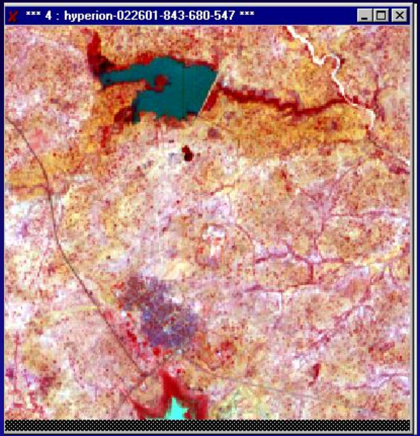
ETM+:4,3,2



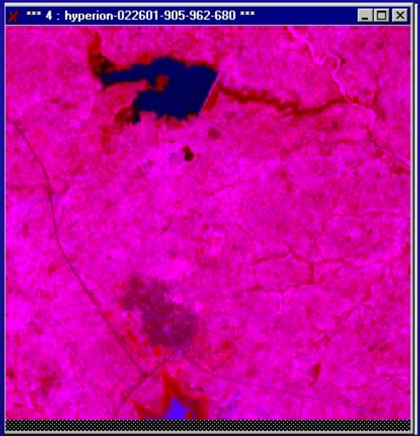
Hyperion:843, 680, 547



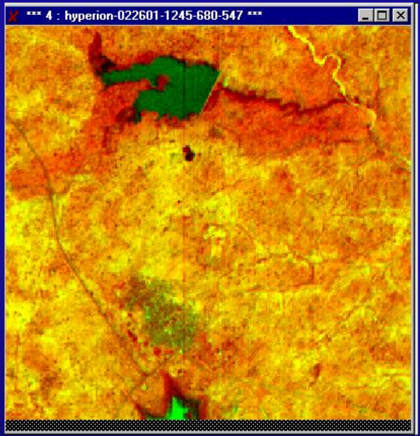
Hyperion: 680, 547, 486



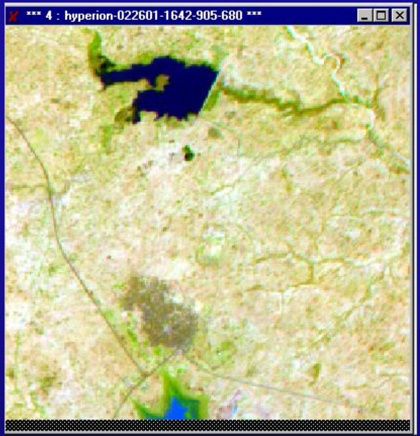
Hyperion:905, 680, 547



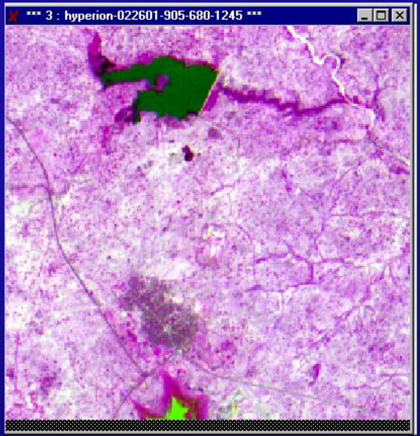
Hyperion:905, 962, 680



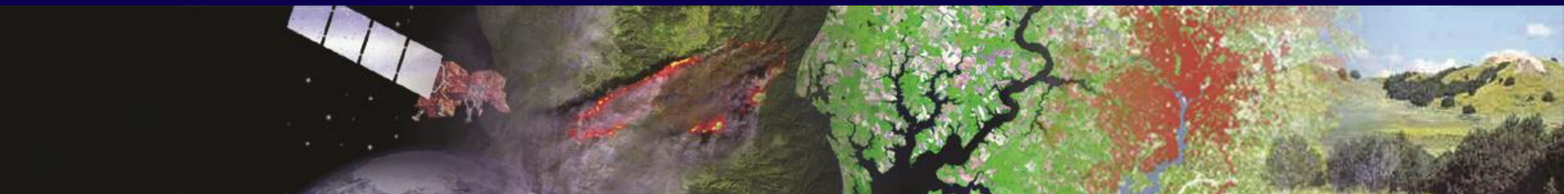
Hyperion:1245, 680, 547



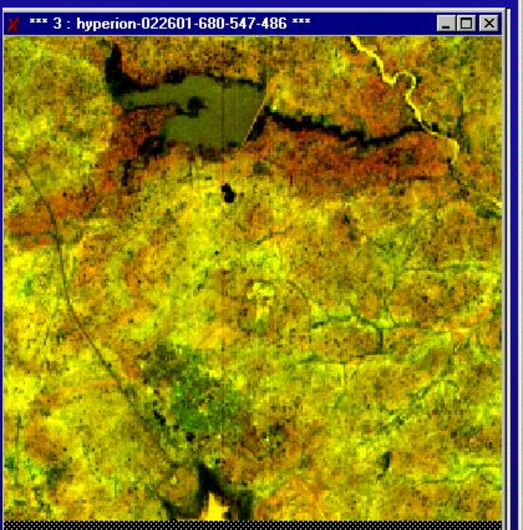
Hyperion:1642, 905, 680



Hyperion:904,680,1245

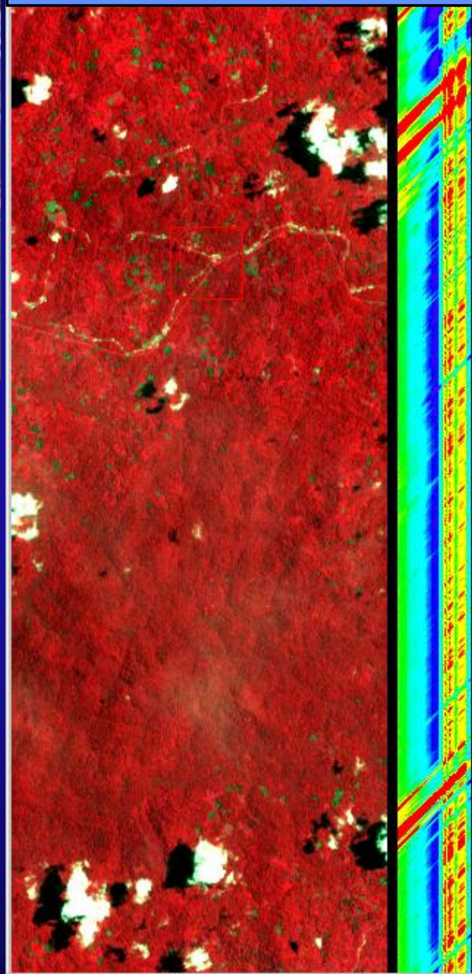


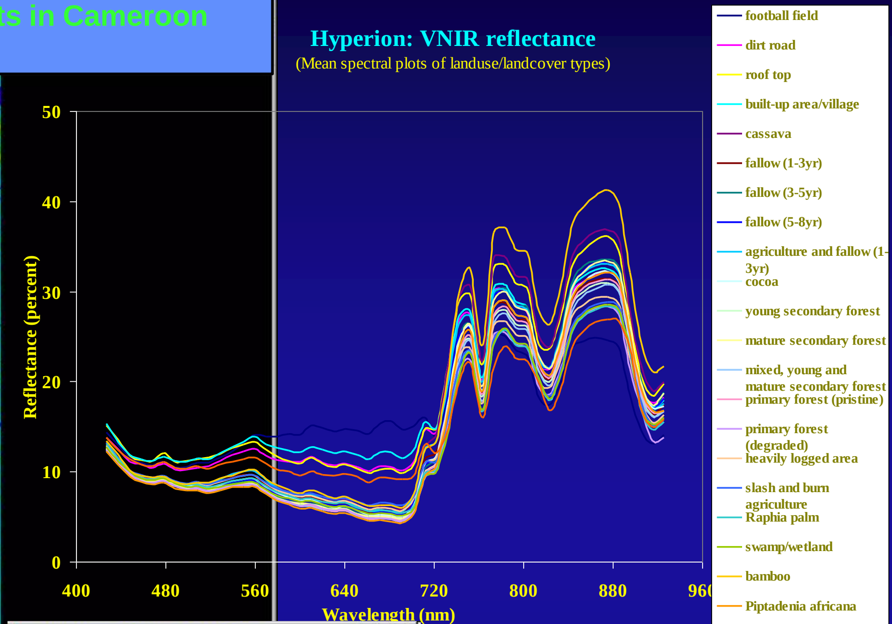
Hyperspectral Remote Sensing of Vegetation
Mega file Data Cube (MFDC) of Hyperion Sensor onboard EO-1

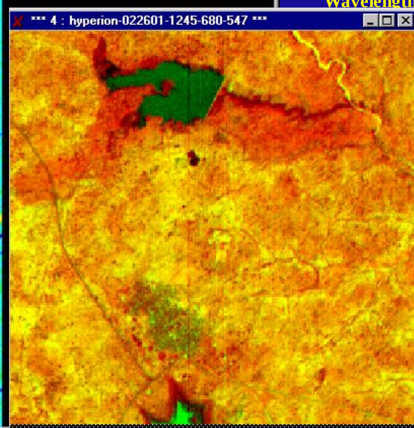


FCC (RGB): 680, 547, 486

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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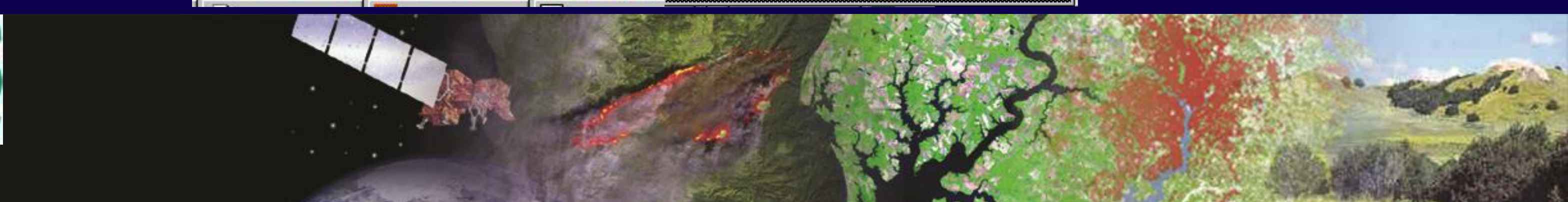

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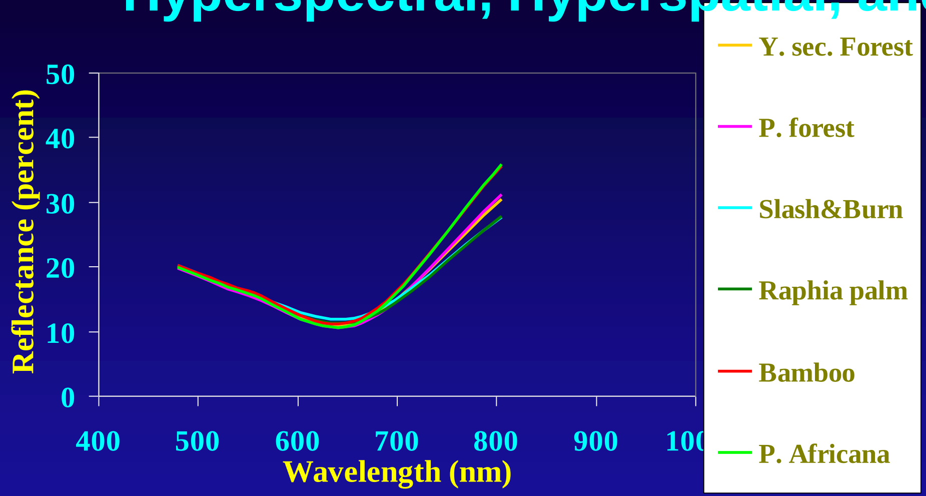
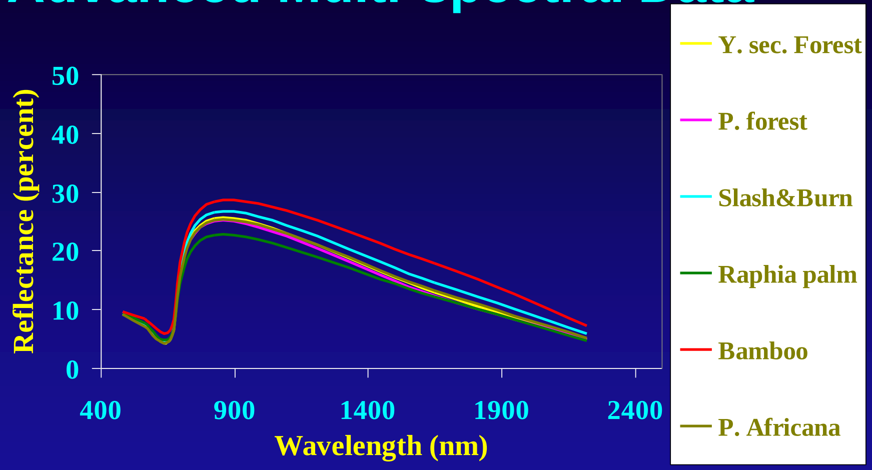
Comparison of Hyperspectral Data with Data from Other Advanced Sensors

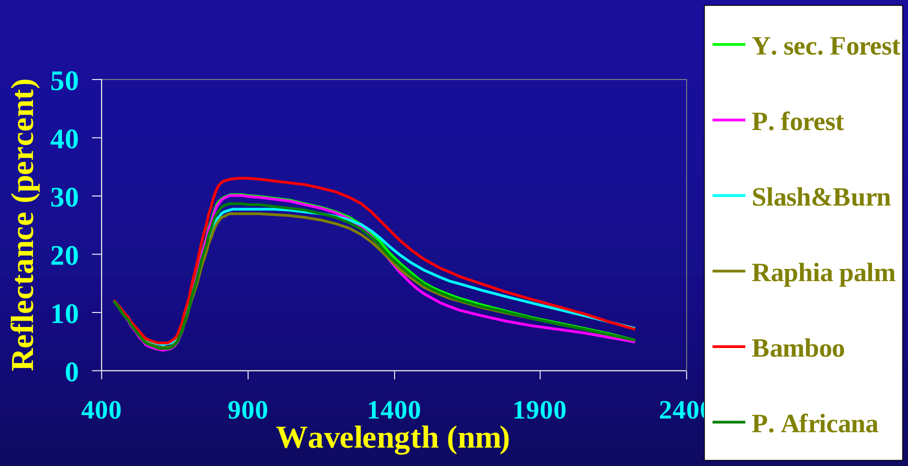
Hyperspectral, Hyperspatial, and Advanced Multi-spectral Data



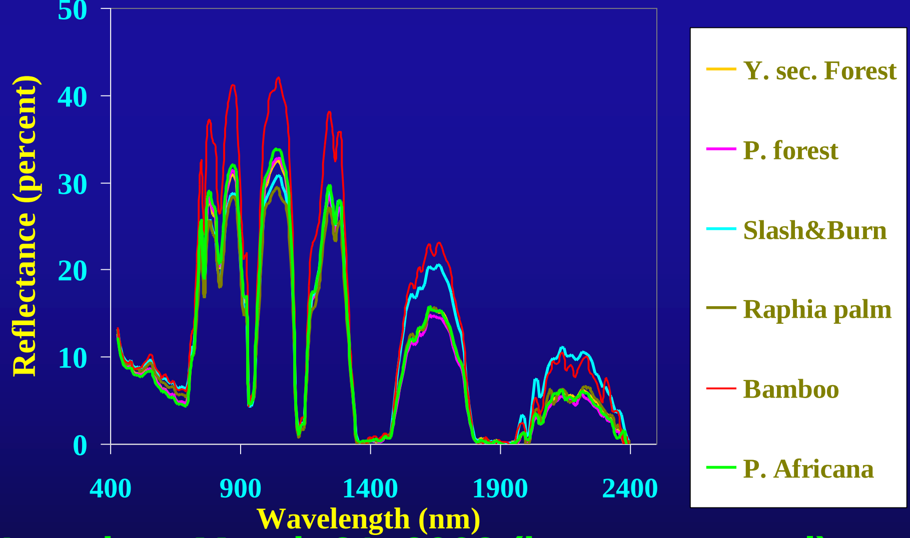
IKONOS: Feb. 5, 2002 (hyper-spatial)



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



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



Hyperion: March 21, 2002 (hyper-spectral)

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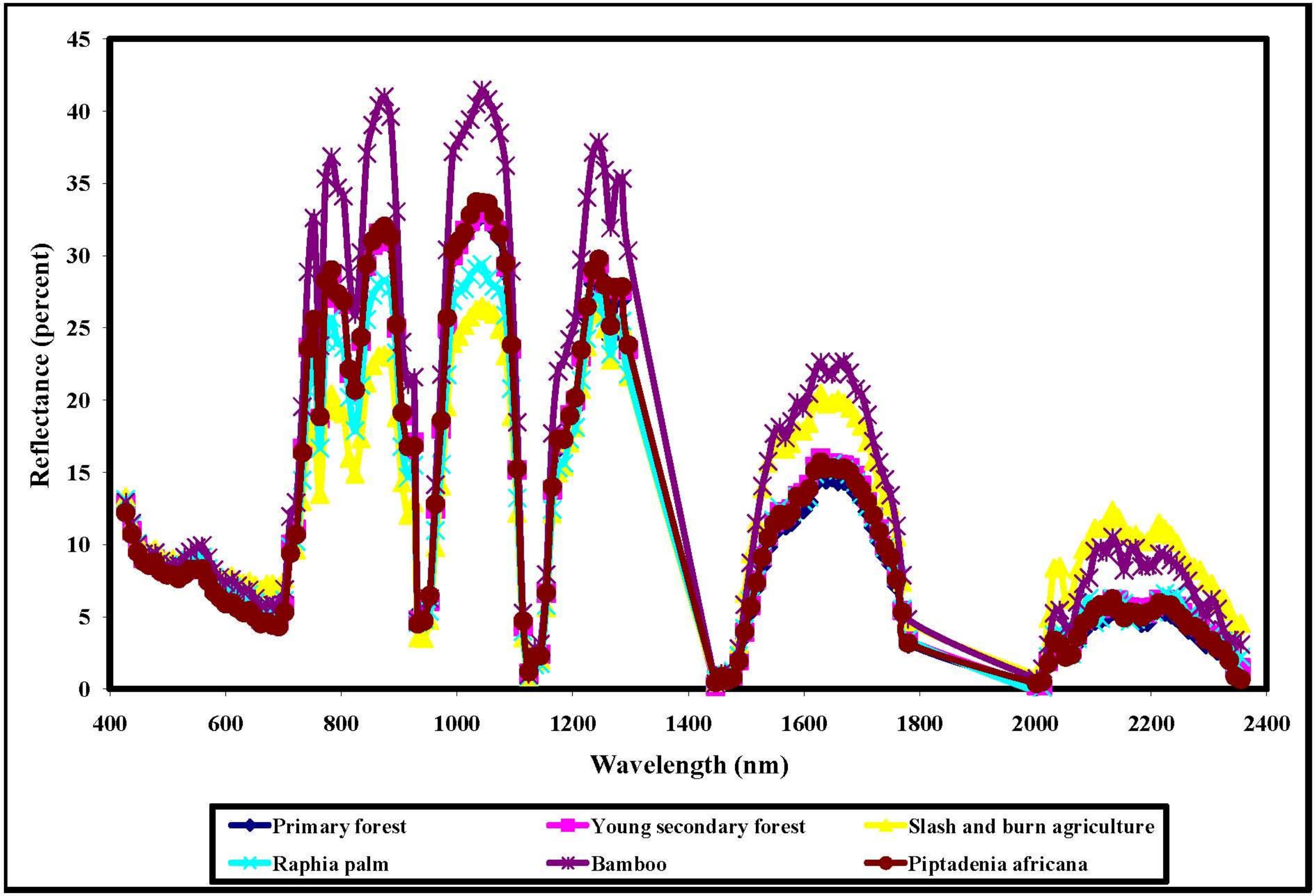
Hyperspectral Data Gathered for the Following Rainforest Vegetation

using Hyperion EO-1 Data



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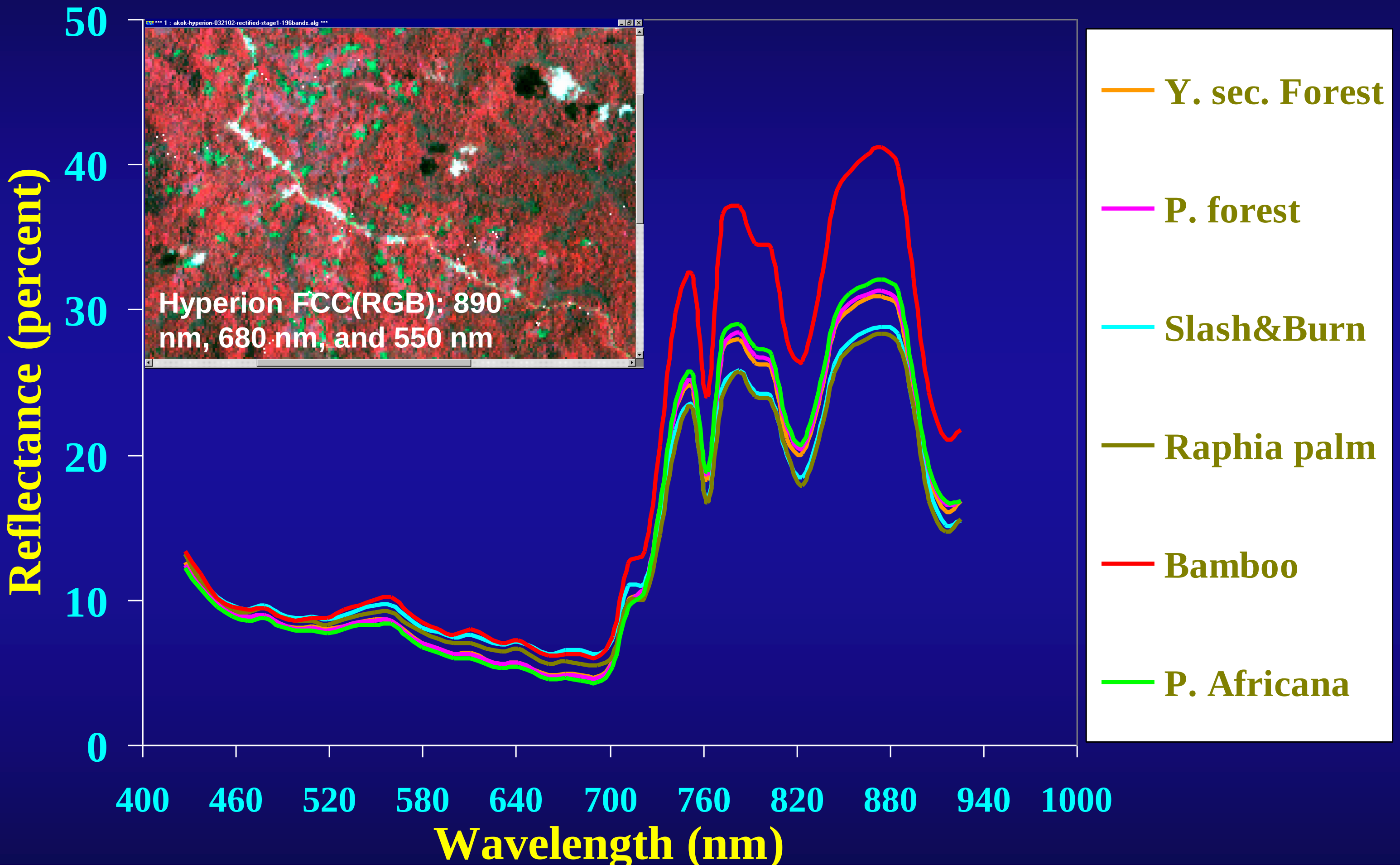
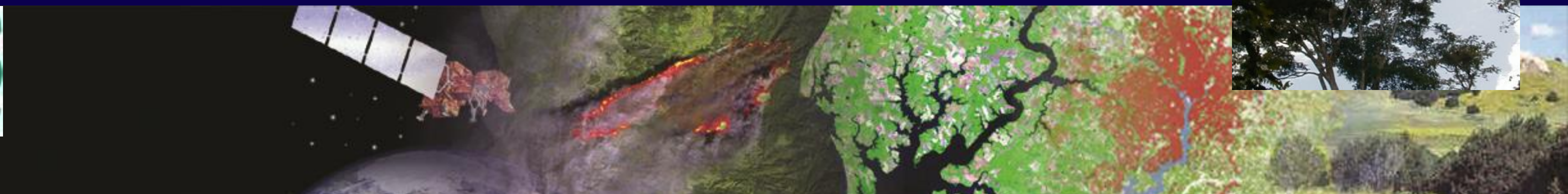
Hyperspectral Data Gathered for the Following Rainforest Vegetation

using Hyperion EO-1 Data





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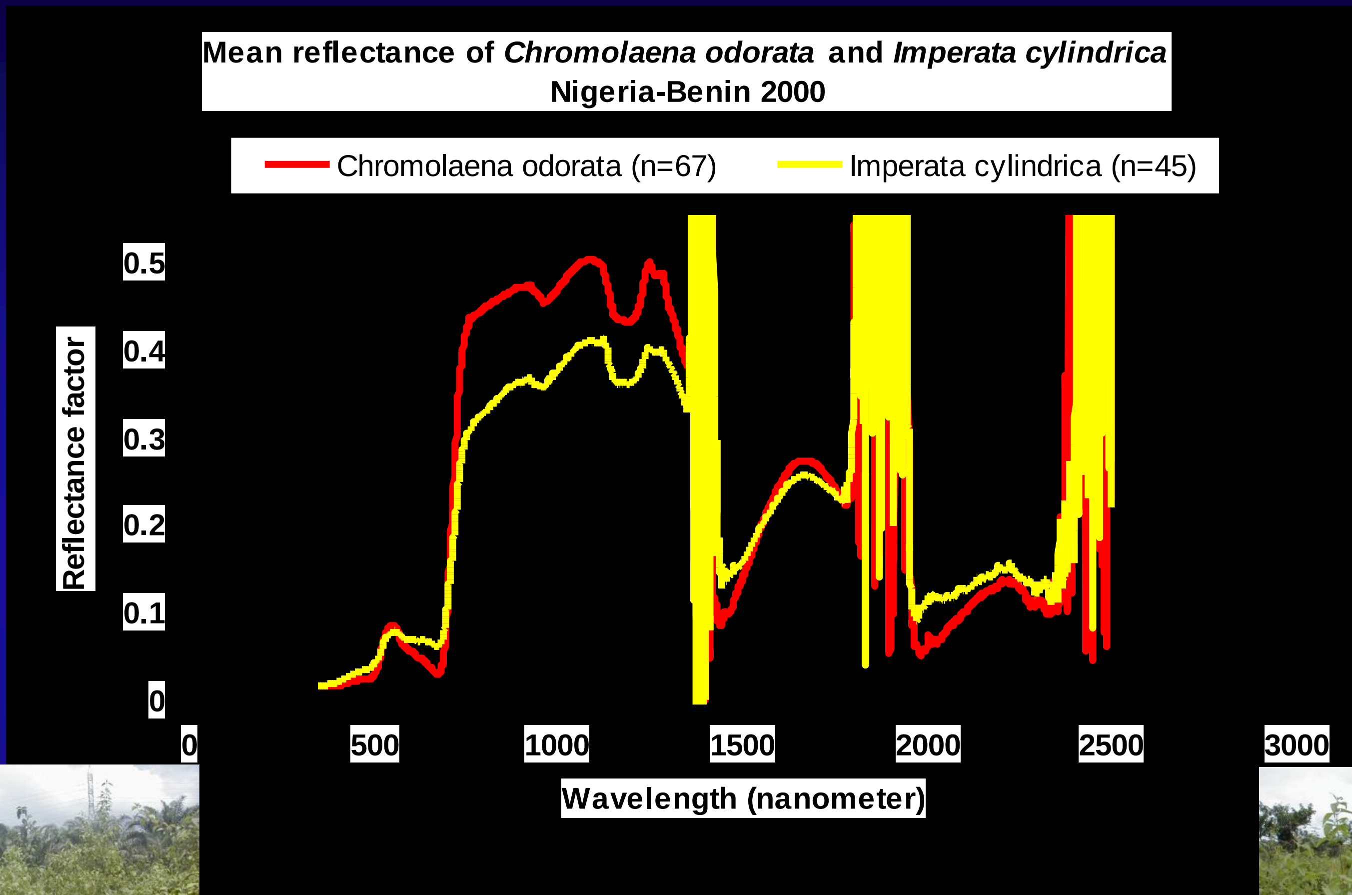
Hyperspectral Data of Two Dominant Weeds

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



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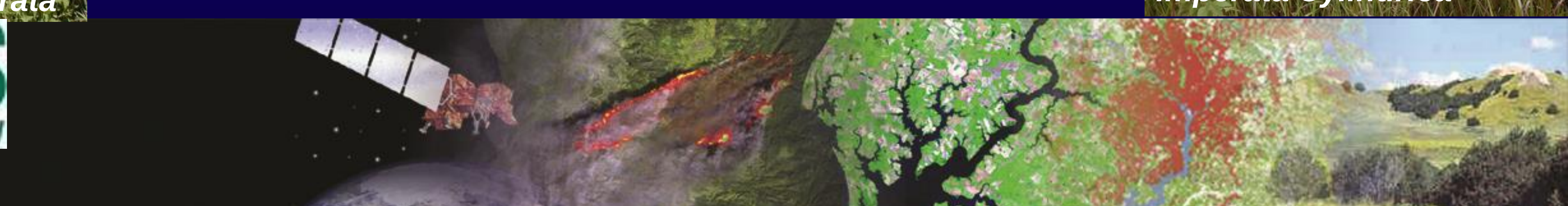
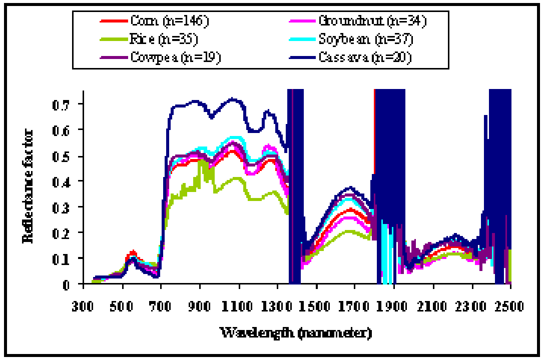
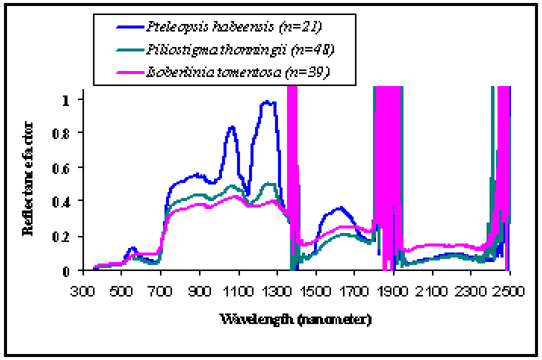


Hyperspectral Data of Vegetation Species and Agricultural Crops

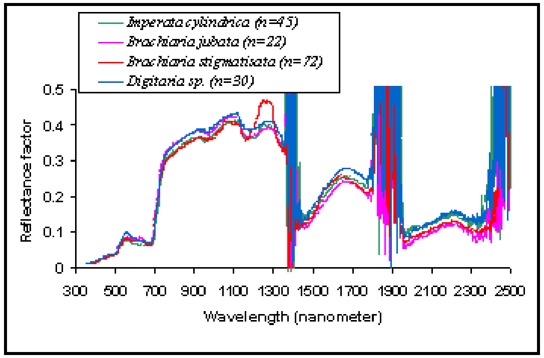
Illustrations for Numerous Vegetation Species from African Savannas



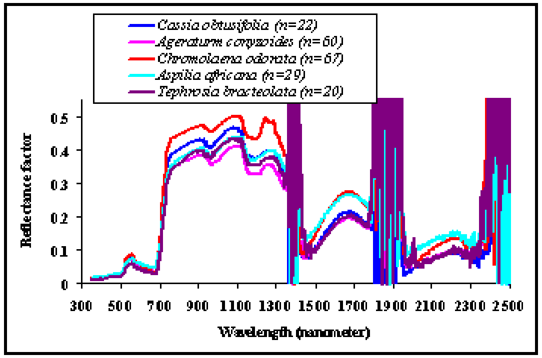
a. Crop species



b. Shrub species



c. Grass species



d. Weed species

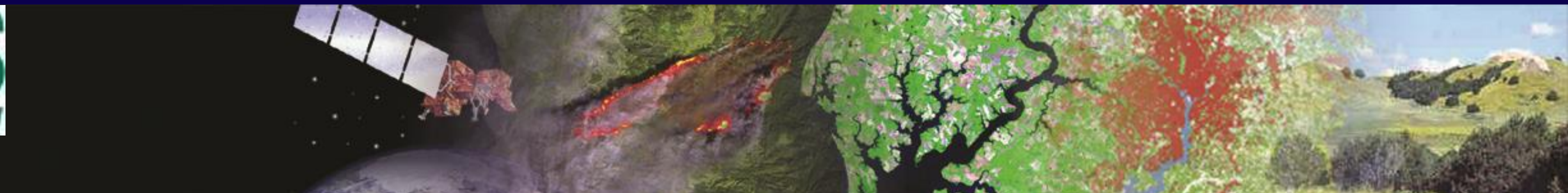
Hyperspectral Data in Study of Complex Vegetation

e.g., Hyperion EO-1 Data for Biochemical Characteristics of African rainforests

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.



Hughes Phenomenon

(or Curse of High Dimensionality of Data) and overcoming data redundancy through Data Mining

Hyperspectral Data (Imaging Spectroscopy data)

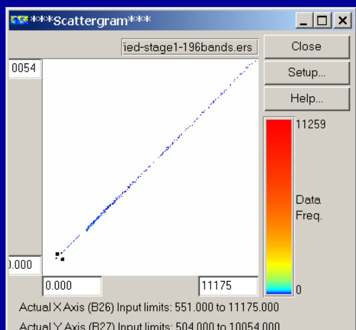
Not a Panacea!

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

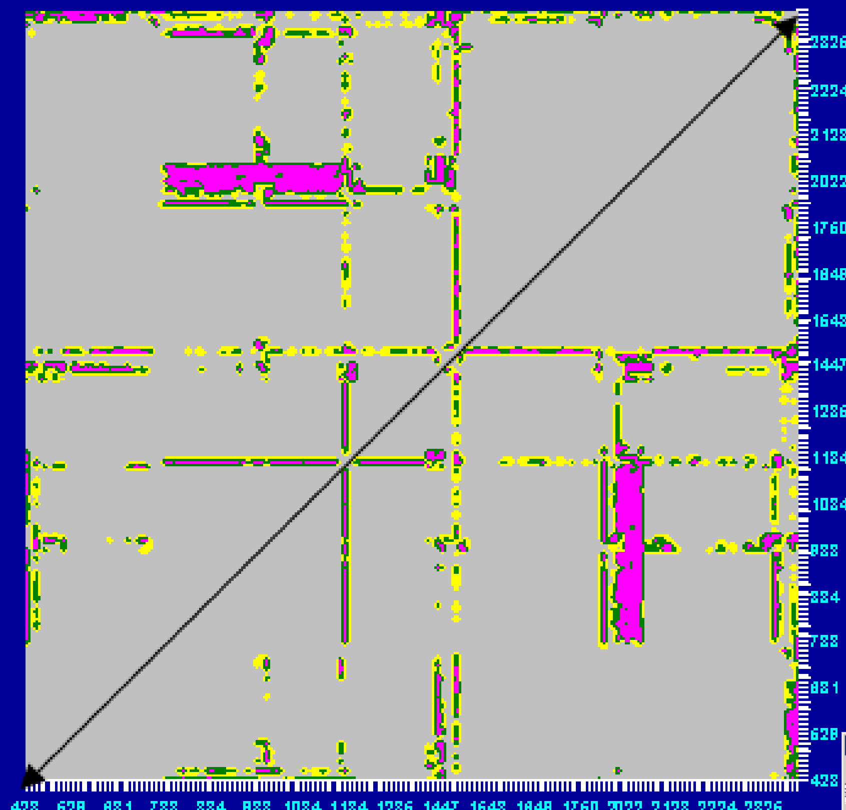
- **data storage volume;**
- **data storage rate;**
- **downlink or transmission bandwidth;**
- **computing bottle neck in data analysis; and**
- **new algorithms for data utilization (e.g., atmospheric correction more complicated).**

Data Mining Methods and Approaches in Vegetation Studies

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

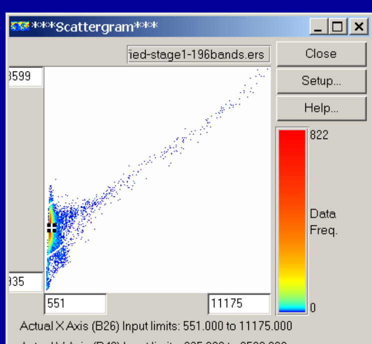


Highly redundant: bands centered at 680 nm and 690 nm



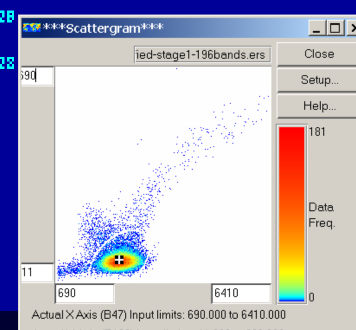
R^2 values between wavebands (lesser the R^2 value lesser the redundancy)

- 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

Lambda vs. Lambda Correlation plot for African rainforest Vegetation



Distinctly different: bands centered at 920 nm and 2050 nm

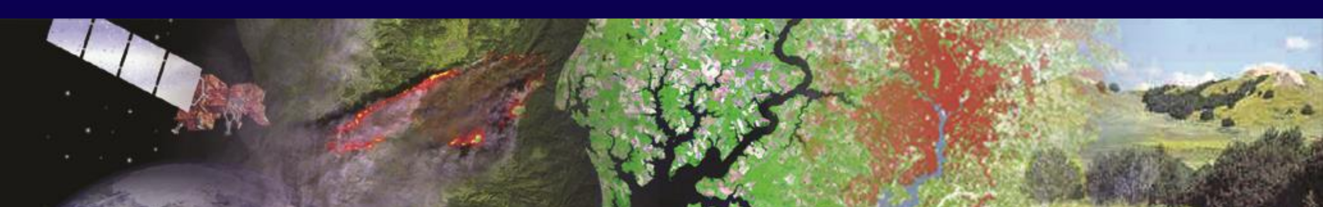
Data Mining Methods and Approaches in Vegetation Studies

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, Band Variance, Information Entropy),
(b) Projection-Based methods (e.g., Principal Component Analysis or PCA, Independent Component Analysis or ICA),
(c) Divergence Measures (e.g., Distance-based measures),
(d) Similarity Measures (e.g., Correlation coefficient, Spectral Derivative Analysis), and
(e) Other Methods (e.g., wavelet Decomposition Method).

Note: see chapter 4



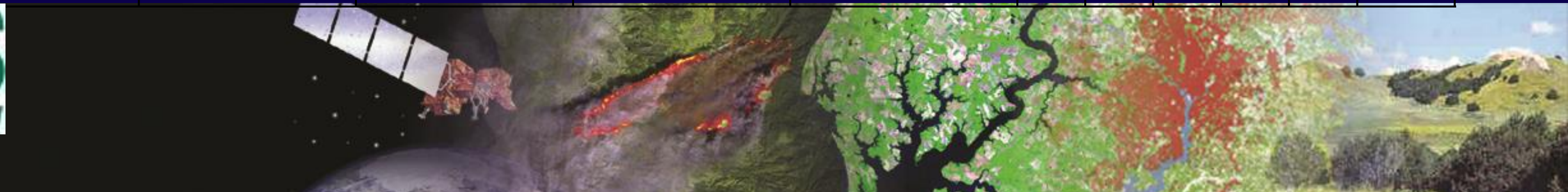
Data Mining Methods and Approaches in Vegetation Studies

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						



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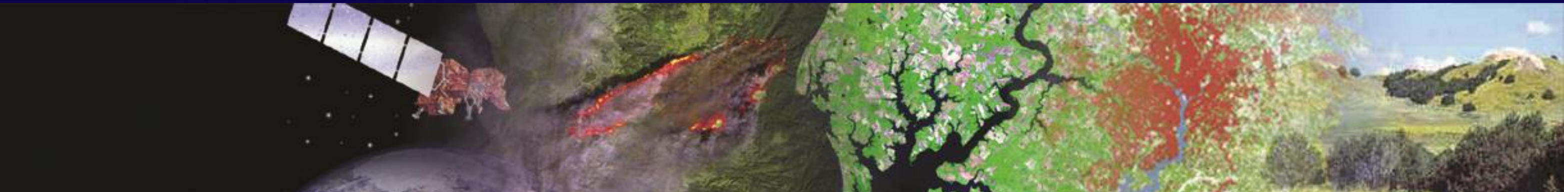
Methods of
Modeling Vegetation Characteristics using
Hyperspectral Vegetation Indices (HVIs)

Methods of Classifying Vegetation Classes or Categories
Using hyperspectral narrowband data

1. Multivariate and Partial Least Square Regression,
2. Discriminant analysis
3. unsupervised classification (e.g., Clustering),
4. supervised approaches
   A. Spectral-angle mapping or SAM,
   B. Maximum likelihood classification or MLC,
   C. Artificial Neural Network or ANN,
   D. Support Vector Machines or SVM,
4. Spectral Matching Technique (SMT)

Excellent for full spectral analysis…..but needs good spectral library

………All these methods have merit; it remains for the user to apply them to the situation of interest.



Hyperspectral Data (Imaging Spectroscopy data)

Hyperspectral Vegetation Indices (HVIs)

Unique Features and Strengths of HVIs

1. **Eliminates redundant bands**

   removes highly correlated bands
2. **Physically meaningful HVIs**

   e.g., Photochemical reflective index (PRI) as proxy for light use efficiency (LUE)
3. **Significant improvement over broadband indices**

   e.g., reducing saturation of broadbands, providing greater sensitivity (e.g., an index involving NIR reflective maxima @ 900 nm and red absorption maxima @680 nm
4. **New indices not sampled by broadbands**

   e.g., water-based indices (e.g., involving 970 nm or 1240 nm along with a nonabsorption band)
5. **multi-linear indices**

   indices involving more than 2 bands

Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Hyperspectral Two-band Vegetation Indices (TBVIs) = 12246 unique indices for 157 useful Hyperion bands of data

$$HTBVI_{ij} = \frac{(R_j - R_i)}{(R_j + R_i)}$$

- **<u>Hyperion</u>:**
- **A. acquired over 400-2500 nm in 220 narrow-bands each of 10-nm wide bands. Of these there are 196 bands that are calibrated. These are: (i) bands 8 (427.55 nm) to 57 (925.85 nm) in the visible and near-infrared; and (ii) bands 79 (932.72 nm) to band 224 (2395.53 nm) in the short wave infrared.**
- **B. However, there was significant noise in the data over the 1206–1437 nm, 1790– 1992 nm, and 2365–2396 nm spectral ranges. When the Hyperion bands in this region were dropped, 157 useful bands remained.**

- **<u>Spectroradiometer</u>:**
- **A. acquired over 400-2500 nm in 2100 narrow-bands each of 1-nm wide. However, 1-nm wide data were aggregated to 10-nm wide to coincide with Hyperion bands.**
- **B. However, there was significant noise in the data over the 1350-1440 nm, 1790-1990 nm, and 2360-2500 nm spectral ranges. was seriously affected by atmospheric absorption and noise. The remaining good noise free data were in 400-1350 nm, and 1440-1790 nm, 1990-2360 nm.**

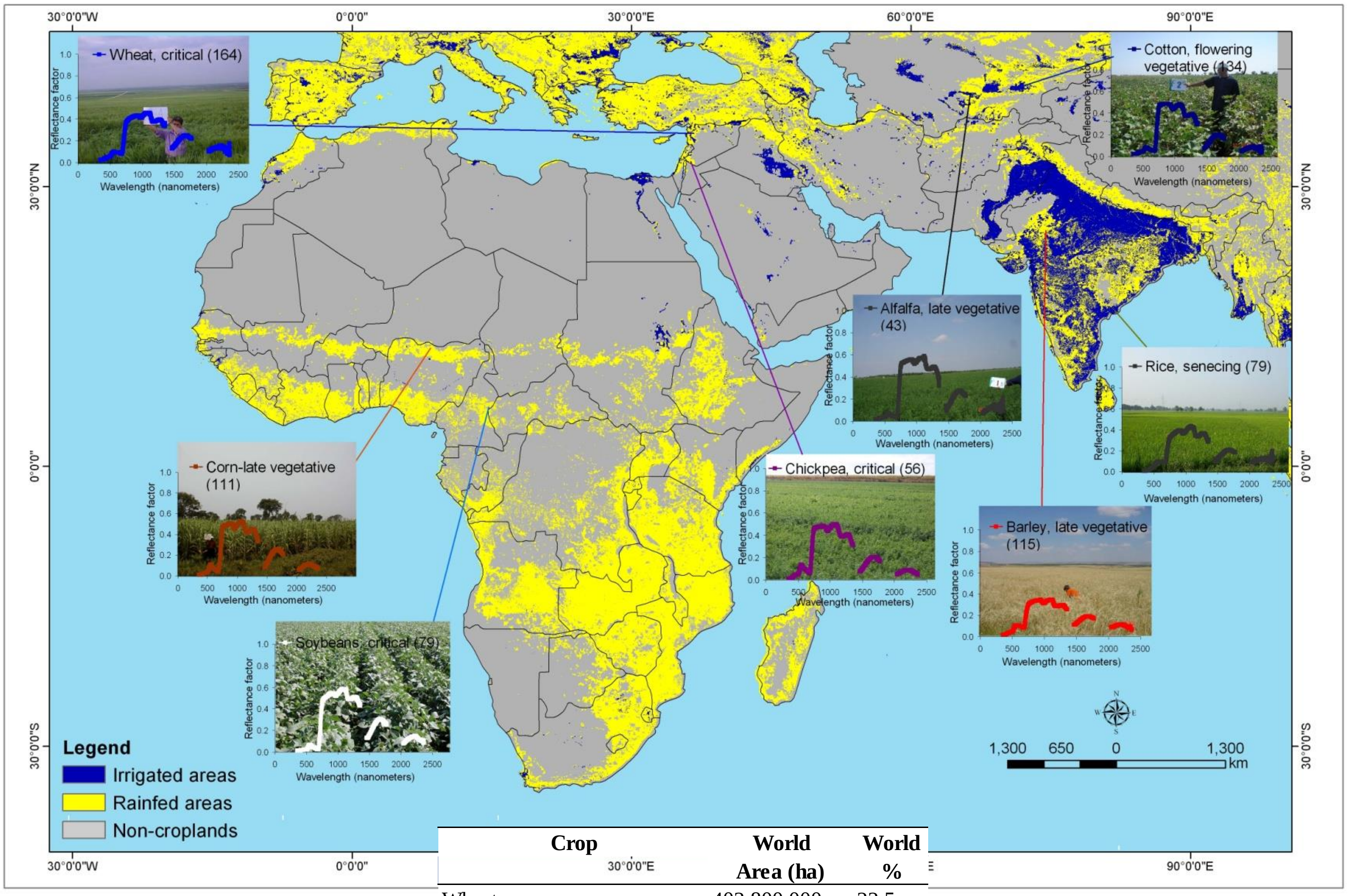
- **……..So, for both Hyperion and Spectroradiometer we had 157 useful bands, each of 10-nm wide, over the same spectral range.**

- **where, i,j = 1, N, with N=number of narrow-bands= 157 (each band of 1 nm-wide spread over 400 nm to 2500 nm), R=reflectance of narrow-bands.**

<u>Model algorithm</u>: two band NDVI algorithm in Statistical Analysis System (SAS). Computations are performed for all possible combinations of λ_1 (wavelength 1 = 157 bands) and λ_2 (wavelength 2 = 157 bands)- <u>a total of 24,649 possible indices</u>. It will suffice to calculate Narrow-waveband NDVI's on one side (either above or below) the diagonal of the 157 by 157 matrix as values on either side of the diagonal are the transpose of one another.

Hyperspectral Study of Agricultural Crops

Hyperspectral Data from Various Benchmark Areas of the World for Leading World Crops



Study areas from where hyperspectral data from spectroradiometer and Hyperion were gathered. The irrigated and rainfed cropland study areas of eight major world crops (Table below) in distinct agroecosystems for which hyperspectral data from spectroradiometer and Hyperion were collected from four study areas (see details in next slide).

Crop	World Area (ha)	World %
Wheat	402,800,000	22.5
Maize	227,100,000	12.7
Rice	195,600,000	10.9
Barley	158,000,000	8.8
Soybeans	92,700,000	5.2
Pulses	79,400,000	4.4
Cotton	53,400,000	3.0
Alfalfa	30,000,000	1.7
Total of major 8 crops (ha)	**1,239,000,000**	69.1
Others (ha)	553,000,000	30.9
Total cropland (ha)	1,792,000,000	100.0

Hyperspectral Study of Agricultural Crops

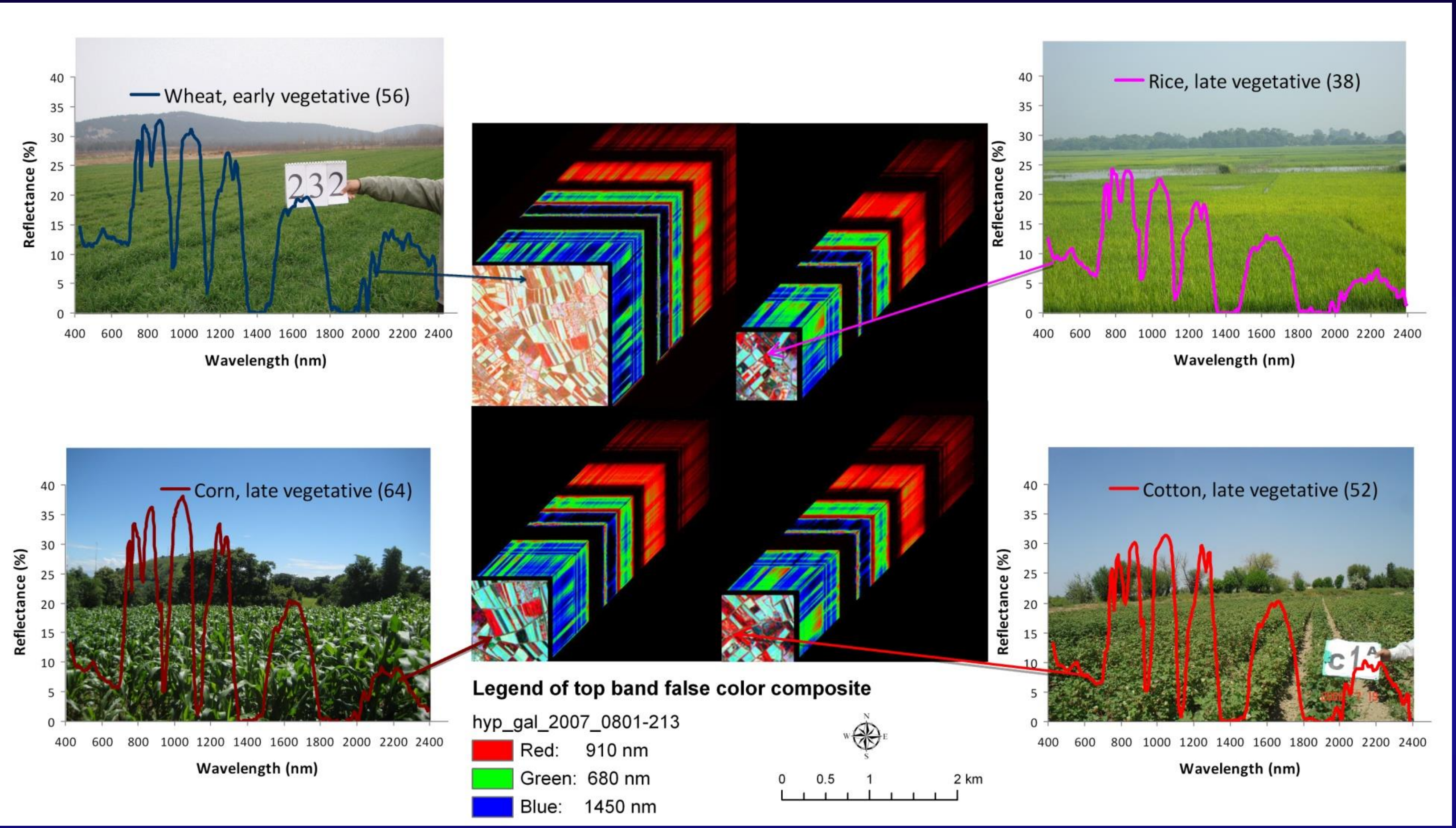
Hyperspectral Data from Various Benchmark Areas of the World for Leading World Crops

Study area (#)	Study areas (name)	Major crops Studied (crop types)	Major crop characteristics for which data gathered (crop parameters)	Hyperspectral data (sensor types)	number of data points (#)
1	Africa (sudan savanna, N. guinea savanna, S. guinea savanna, derived savanna, humid forests)	corn, soybeans rice	biomass plant height, plant density, crop types	Hyperion spectroradiometer	532
2	Syria (supplemental irrigated areas)	Barley, corn, soybeans, wheat, pulses (chickpea)	biomass, LAI, Yield, plant height, plant density, nitrogen, crop types	spectroradiometer,	467
3	Uzbekistan (irrigated areas)	wheat, rice, cotton, alfalfa, corn	biomass, Yield, plant height, plant density, crop types	Hyperion spectroradiometer	372
4	India (rainfed areas)	barley, soybeans, pulses (chickpea)	biomass plant height, plant density, crop types	Hyperion spectroradiometer	182

Cross-site hyperspectral spectroradiometer data. Cross-site mean (regardless of which study site (1-4, Table)) spectral plots of eight leading world crops in various growth stages. (A) Four crops at different growth stages; (B) same four crops as in A but in different growth stages; (C) four more crops at early growth stages; and (D) same four crops as C, but at different growth stages. Note: numbers in bracket are sample sizes.

Hyperion Hyperspectral Study of Agricultural Crops

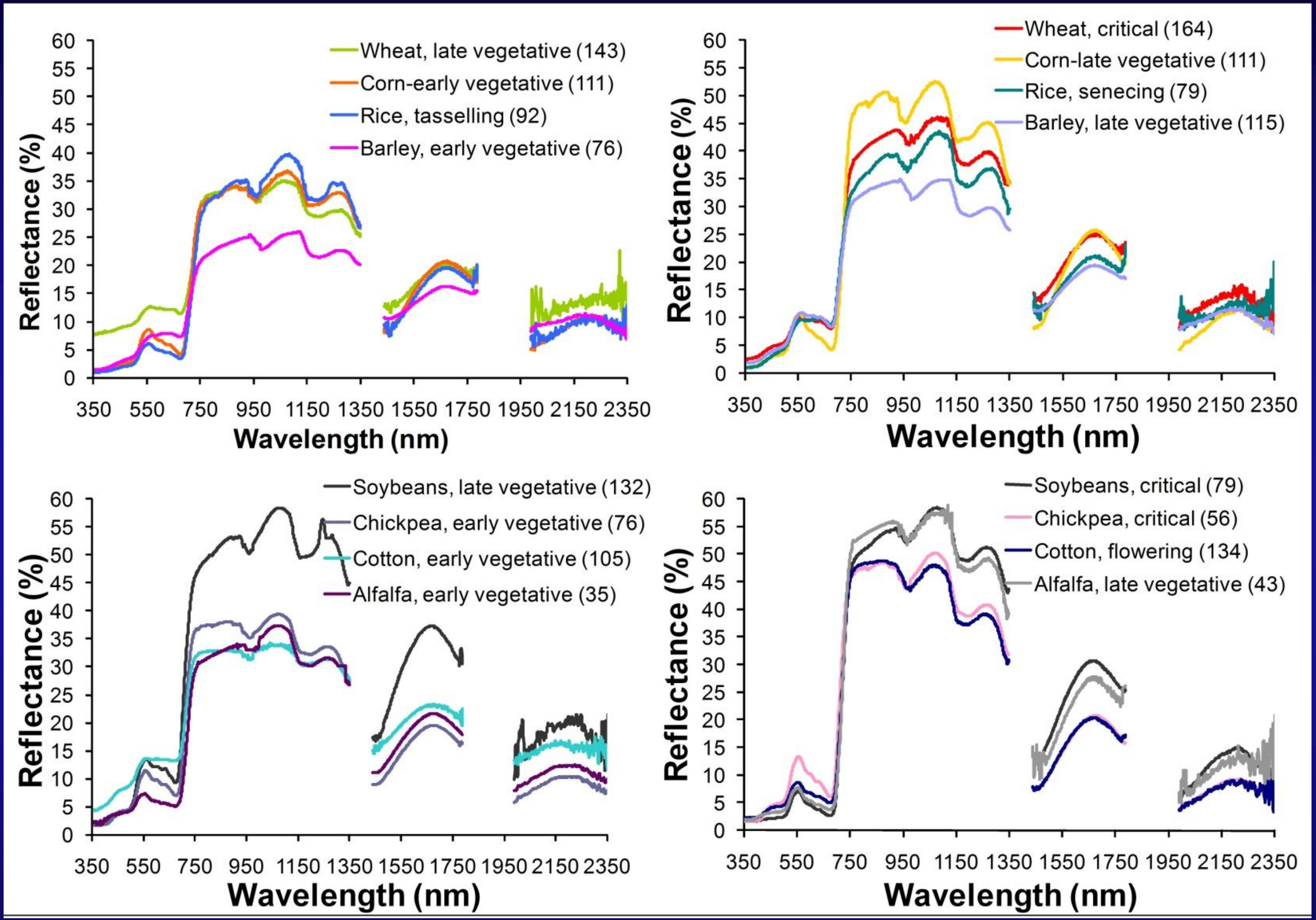
Hyperspectral Data from Various Benchmark Areas of the World for Leading World Crops



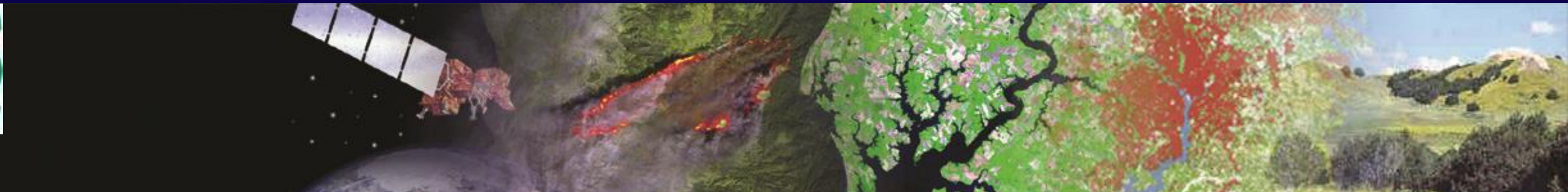
Hyperion data of crops illustrated for typical growth stages in the Uzbekistan study area. The Hyperion data cube shown here is from a small portion of one of the two Hyperion images. The Hyperion spectra of crops are gathered from different farm fields in the two images and their average spectra illustrated here along with the sample sizes indicated within the bracket. The field data was collected within two days of the image acquisition.

Hyperspectral Study of Agricultural Crops

Hyperspectral Data from Various Benchmark Areas of the World for Leading World Crops



Cross-site hyperspectral spectroradiometer data. Cross-site mean (regardless of which study site (1-4, Table 2)) spectral plots of eight leading world crops in various growth stages. (A) Four crops at different growth stages; (B) same four crops as in A but in different growth stages; (C) four more crops at early growth stages; and (D) same four crops as C, but at different growth stages. Note: numbers in bracket are sample sizes.



Hyperspectral Remote Sensing of Vegetation

Spectral Wavelengths and their Importance in the Study of Vegetation in different Growth Stages

Figure 3a. Cotton in critical growth stage.

(a) Cotton (critical)


Figure 3c. Soybeans in critical growth stage.

(b) Soybeans (early)


Figure 3e. Potato in early growth stage.

(c) Potato (early)

Figure 3b. Cotton in yielding/harvest

(a) Cotton (flowering/senescing)

Figure 3d. Soybeans in flowering growth stage.

(b) Soybeans (critical)

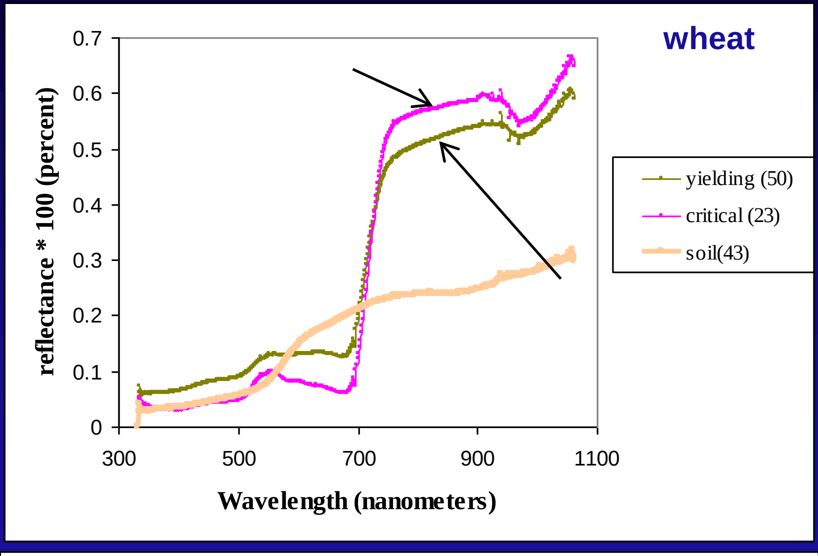

Figure 3f. Potato in late growth stage.

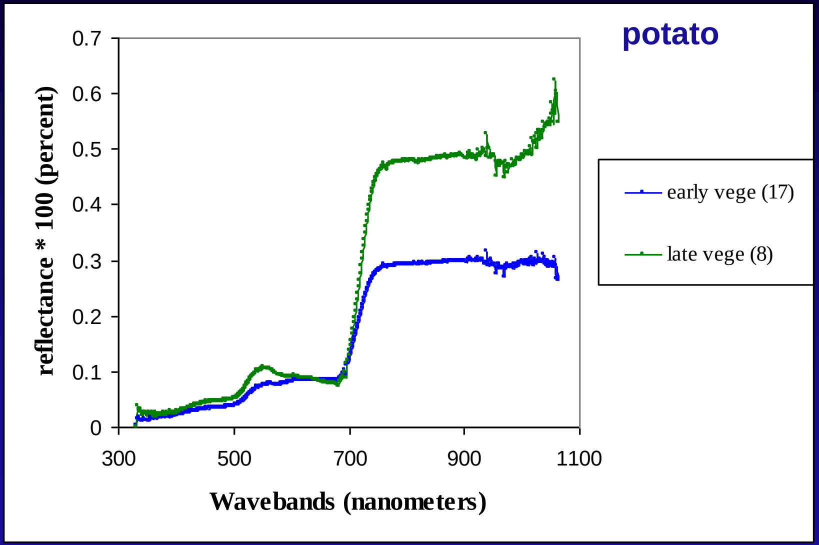
(c) Potato (mid-vegetative)

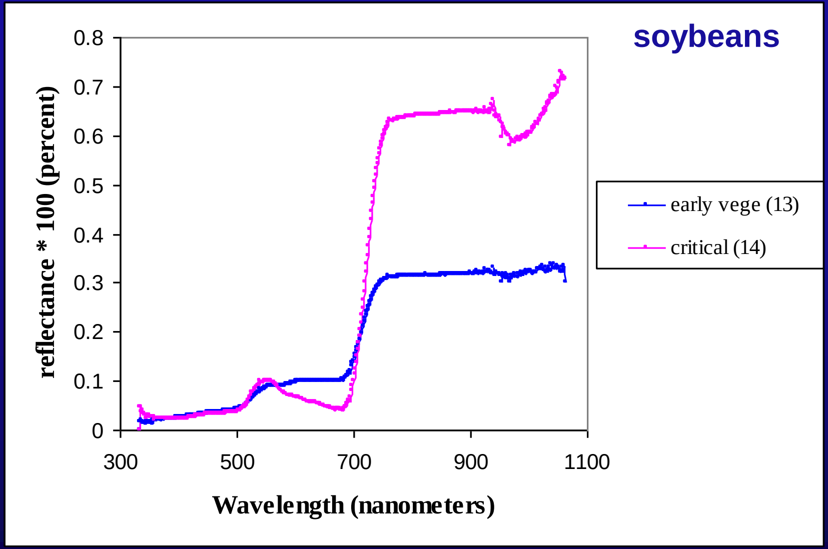
Data was Gathered at Various Growth Stages

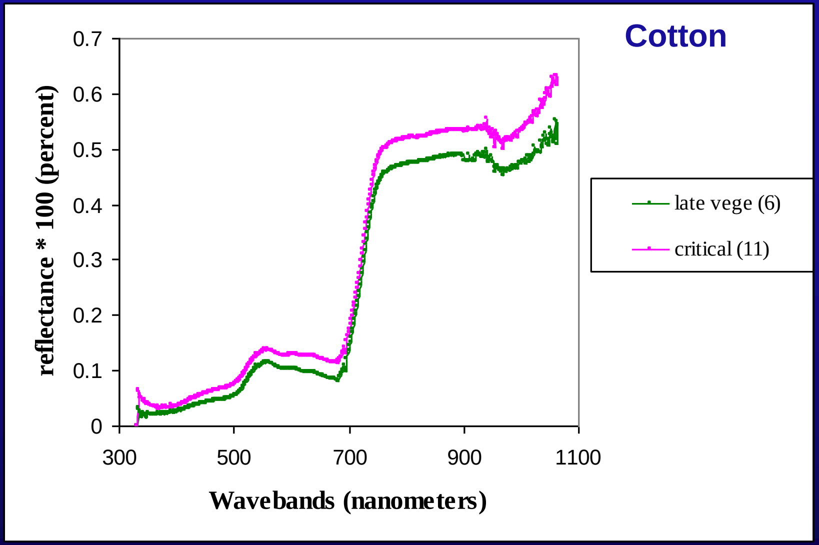
Hyperspectral Remote Sensing of Vegetation

Spectral Wavelengths and their Importance in the Study of Vegetation in different Growth Stages









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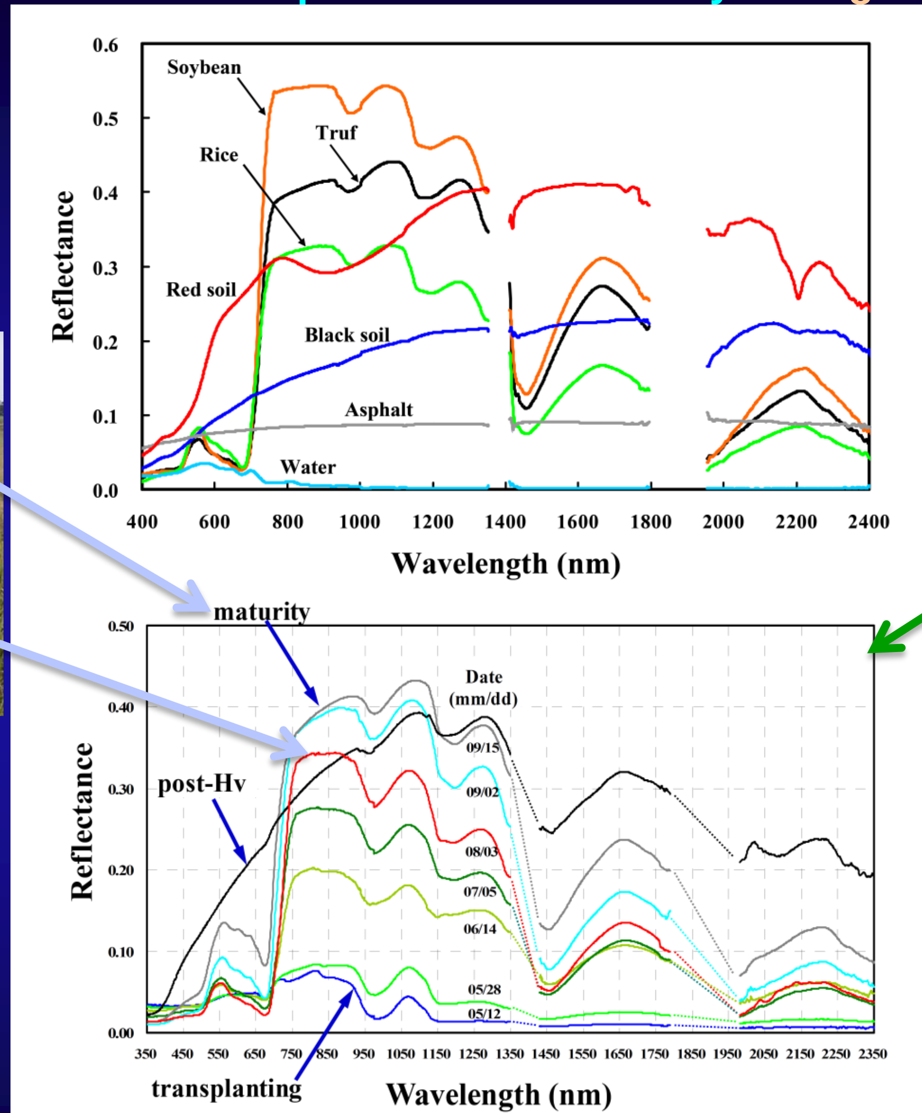
Hyperspectral Remote Sensing of Vegetation

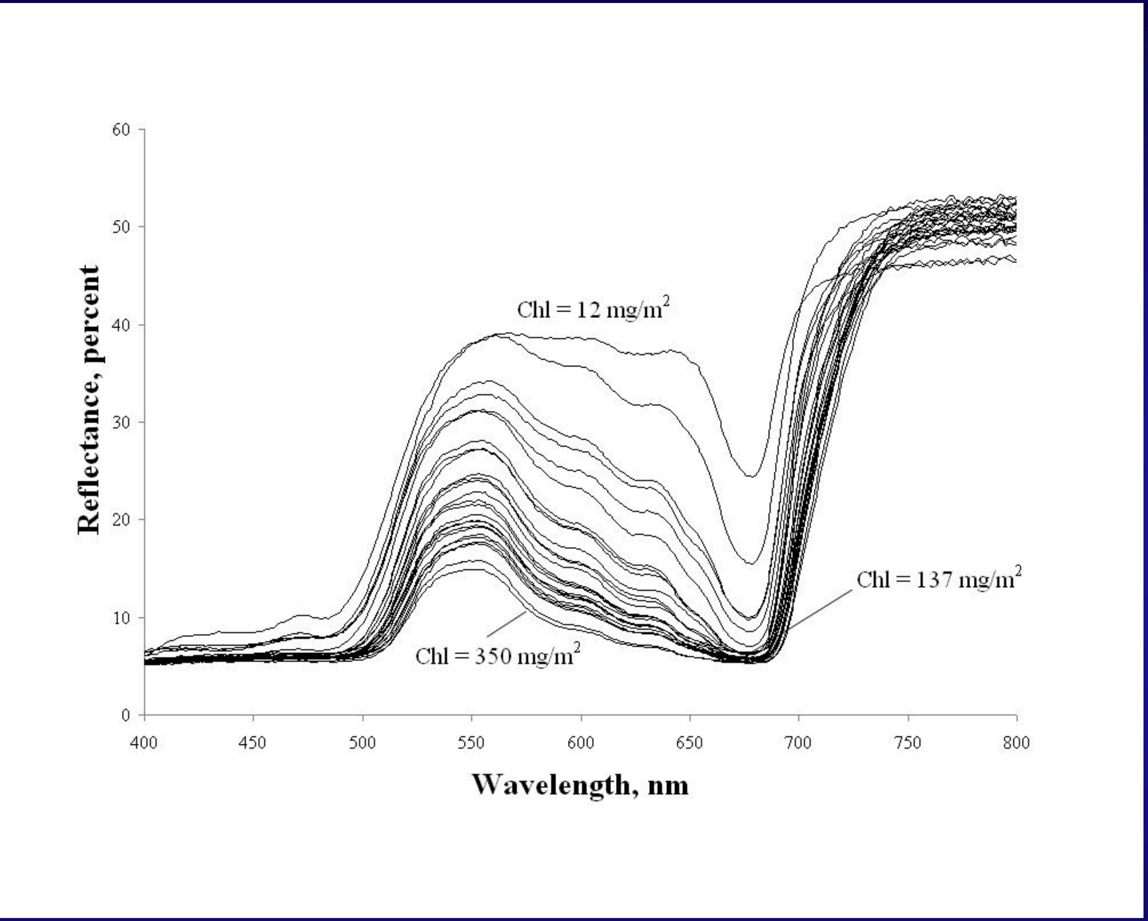
Spectral Wavelengths and their Importance in the Study of Vegetation over Time



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

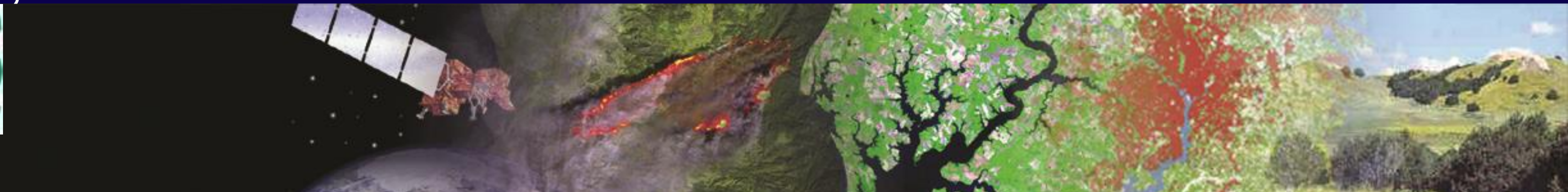
Hyperspectral Remote Sensing of Vegetation

Study of Pigments: chlorophyll



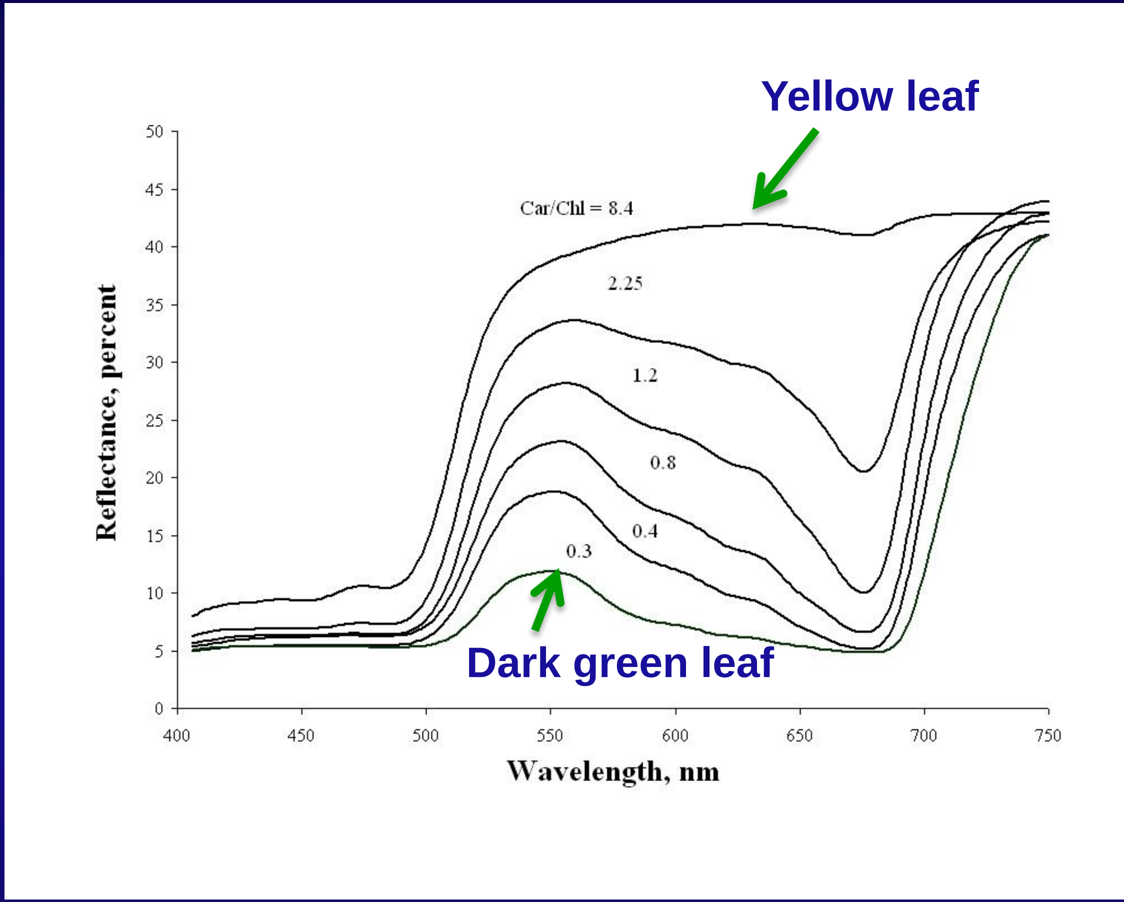
e.g., Reflectance spectra of beech leaves…red-edge (700-740 nm) one of the best.

Note: see chapter 6; Gitelson et al.



Hyperspectral Remote Sensing of Vegetation

Study of Pigments: carotenoids/chlorophyll

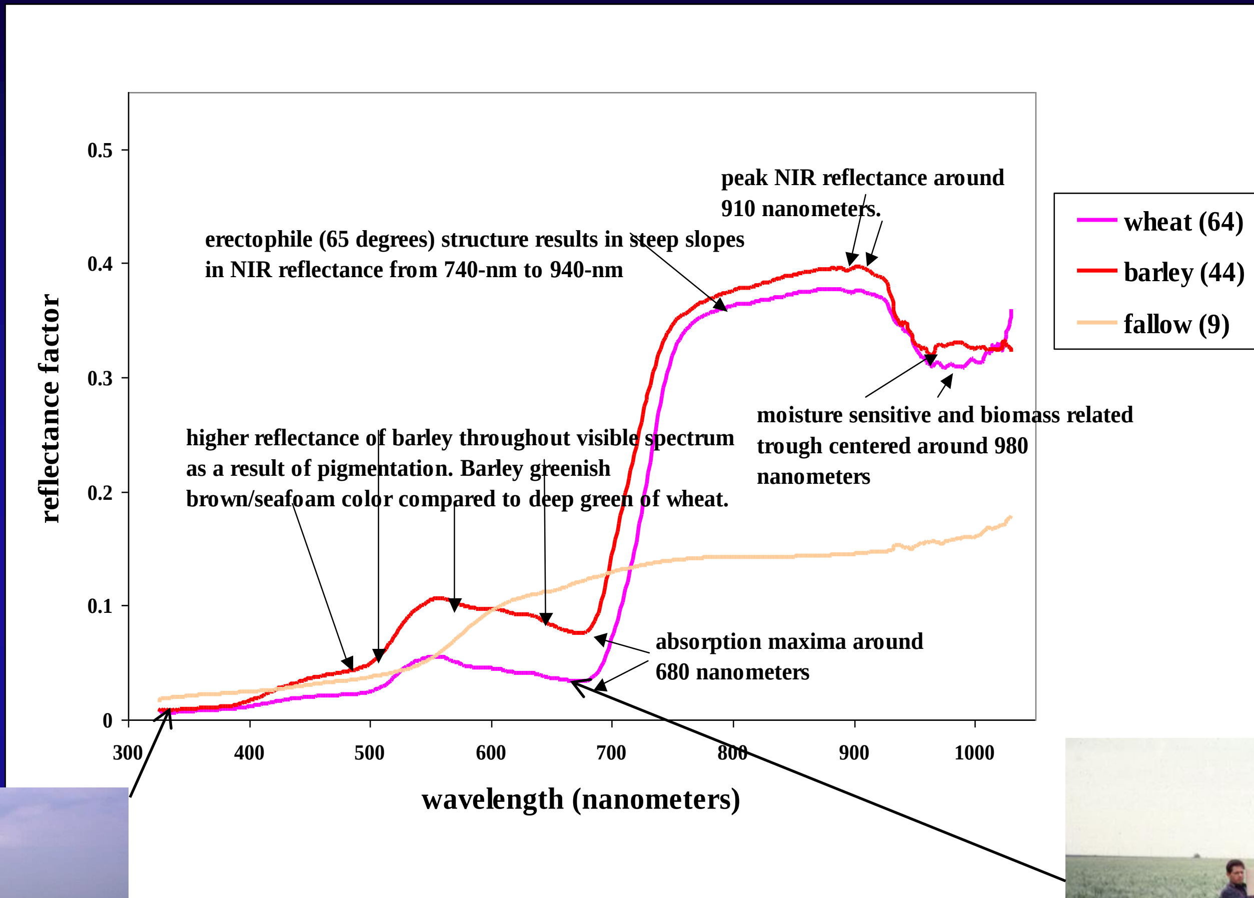


e.g., Reflectance spectra of chestnut leaves…difference reflectance of (680-500 nm)/750 nm quantitative measurement of plant senescence

Note: see chapter 6; Gitelson et al.

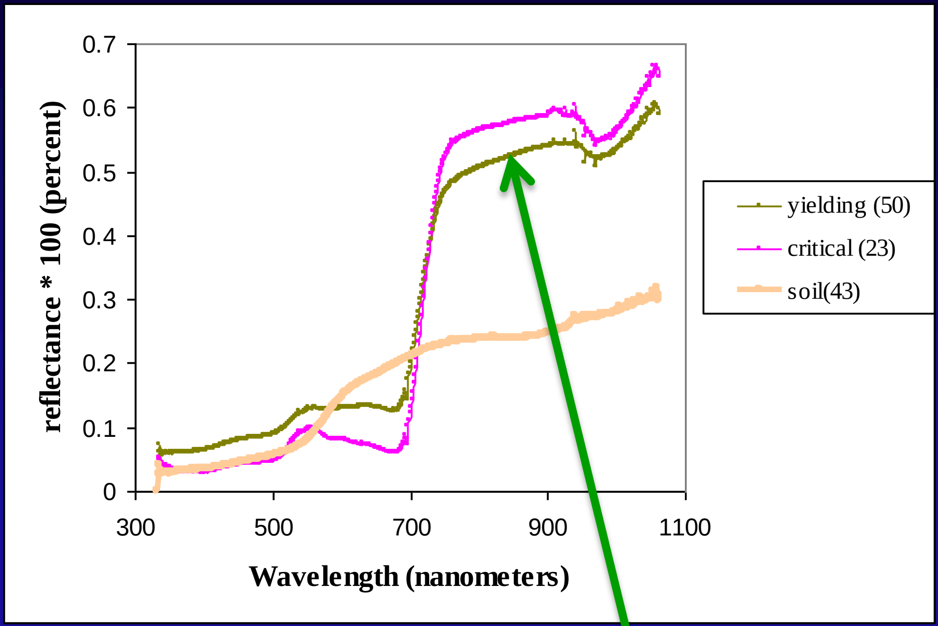
Wheat Crop Versus Barley Crop Versus Fallow Farm

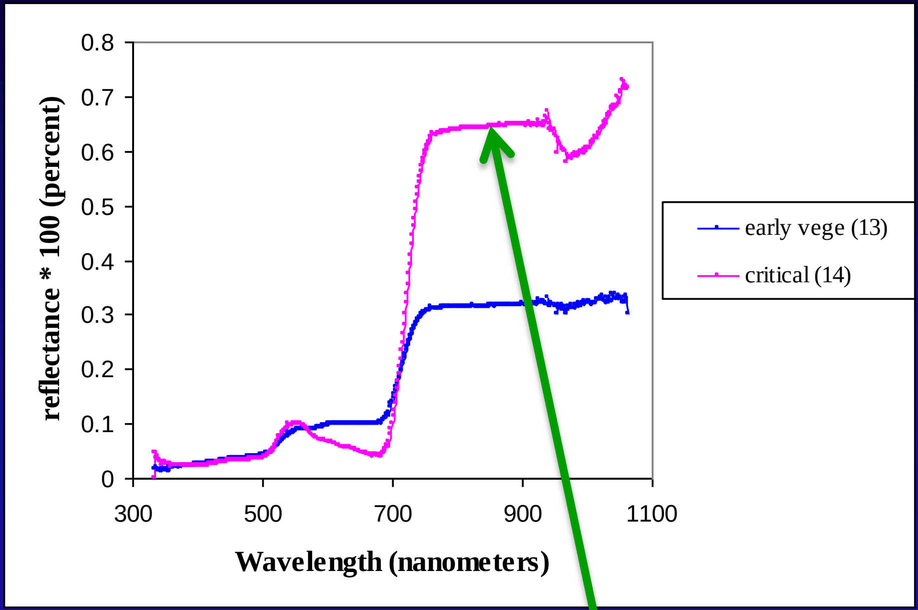
Hyperspectral narrow-band Data for an Erectophile (65 degrees) canopy Structure

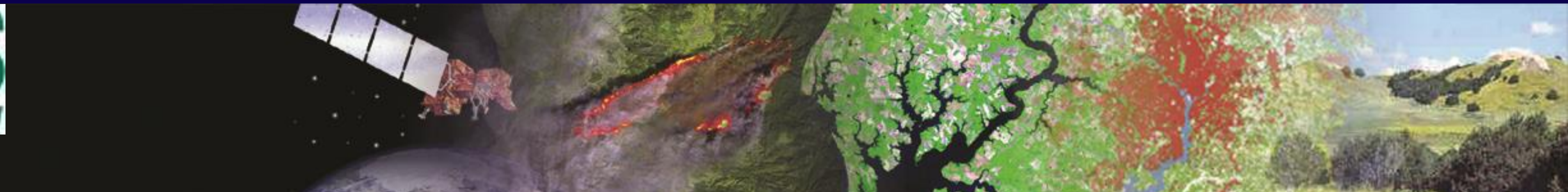


Hyperspectral Remote Sensing of Vegetation

Spectral Wavelengths and their Importance in the Study of Vegetation Structure





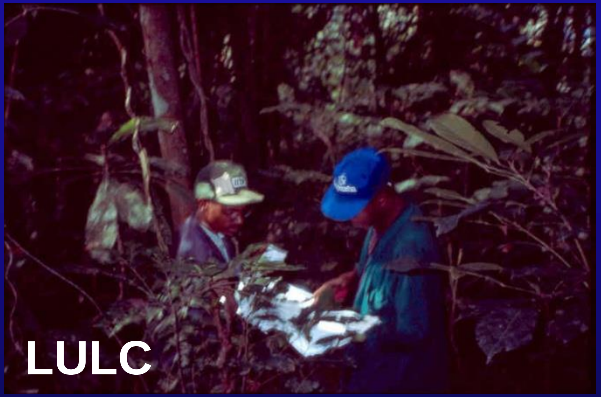


Rainforest Vegetation Studies: biomass, tree height, land cover, species in African Rainforests

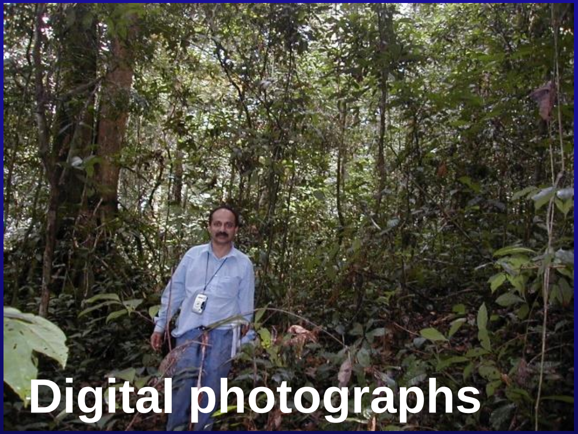

Fallows biomass

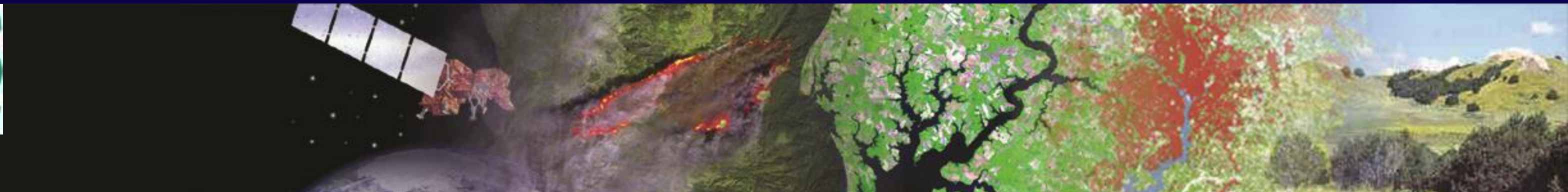

dbh


Tree height


LULC

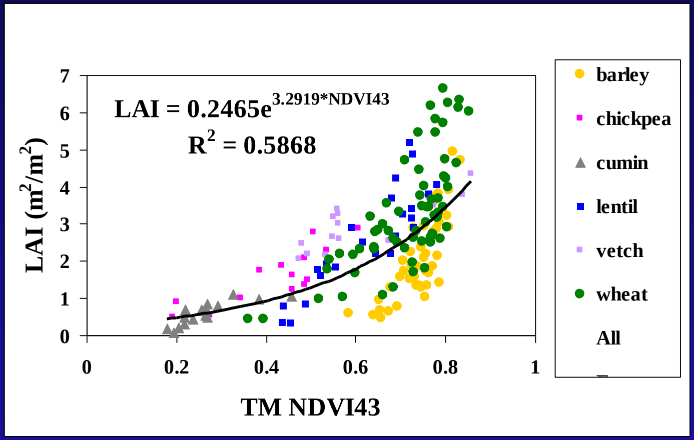

Road network and logging


Digital photographs

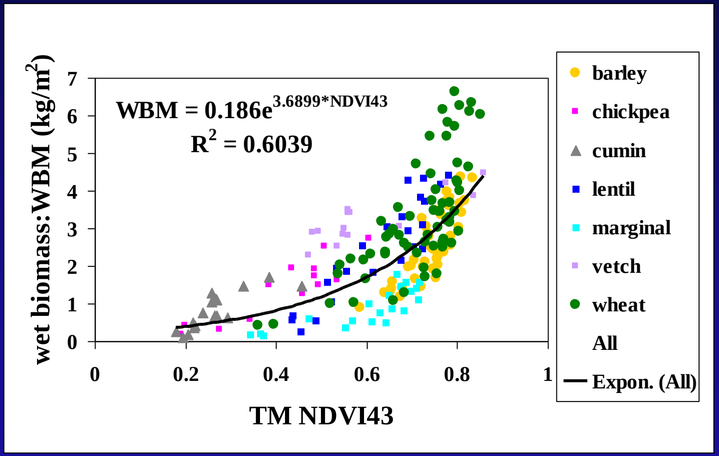


Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Non-linear biophysical quantities (e.g., biomass, LAI) vs.:(a)Broadband models (top two), & (b)Narrowband HTBVI models (bottom two)

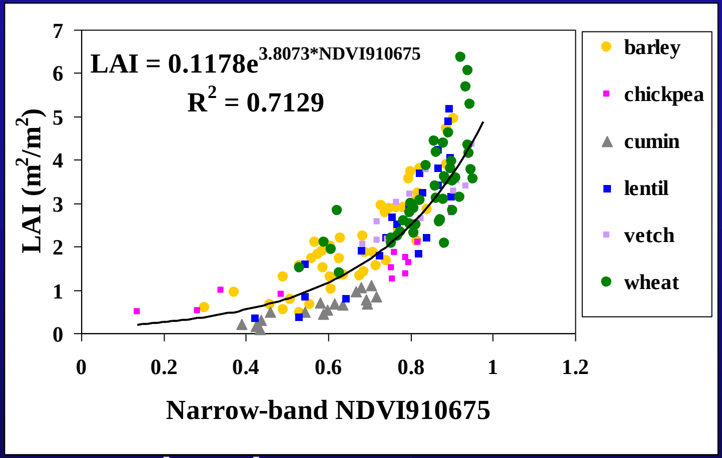


broad-band NDVI43 vs. LAI

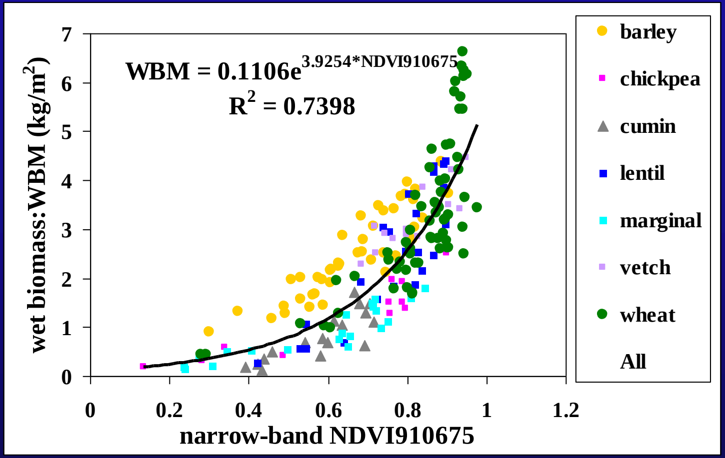


broad-band NDVI43 vs. WBM

HTBVIs explain about 13 percent Greater Variability than Broad-band TM indices in modeling LAI and biomass



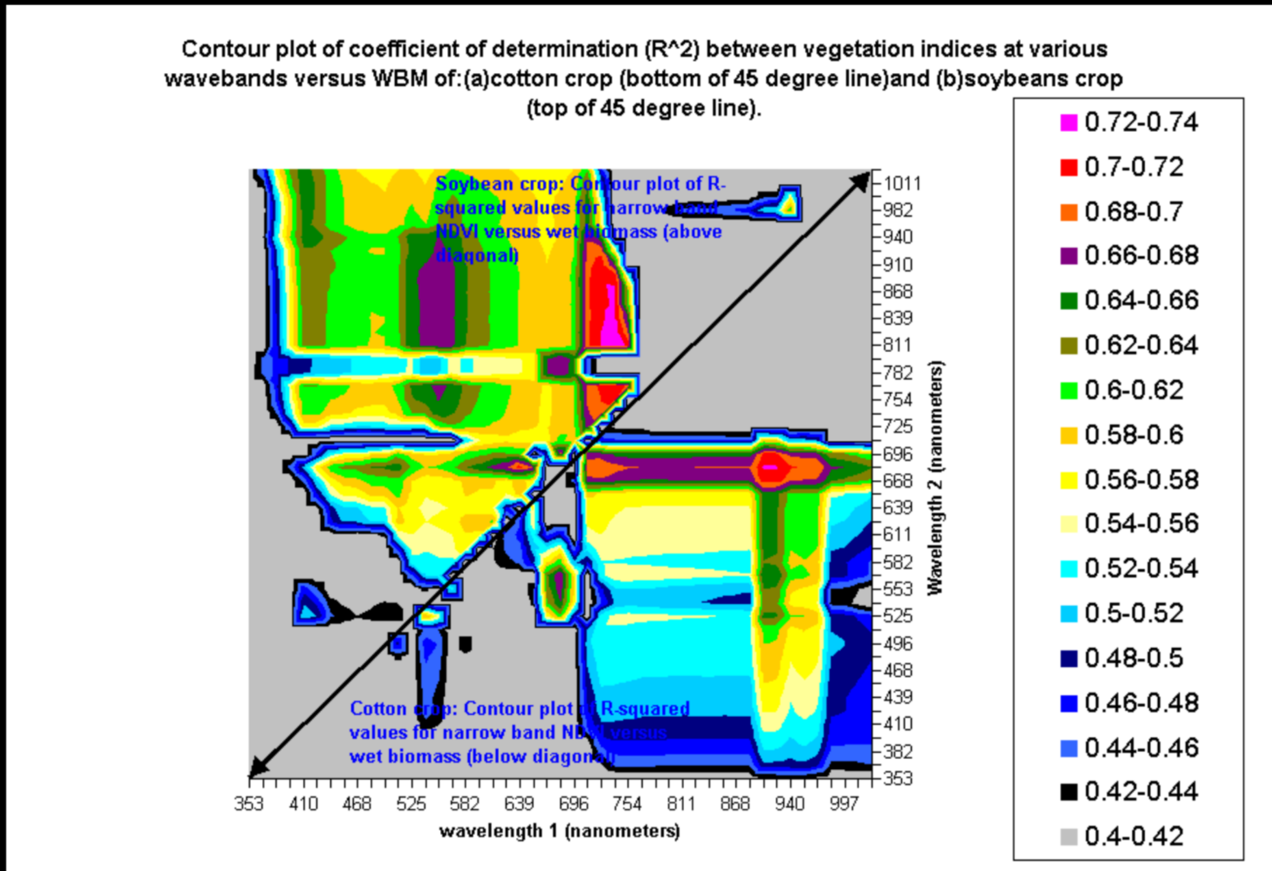
narrow-band NDVI43 vs. LAI



narrow-band NDVI43 vs. WBM

Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Lambda vs. Lambda R-square contour plot on non-linear biophysical quantity (e.g., biomass) vs. HTBVI models



Illustrated for 2 crops here

Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Hyperspectral Two-band Vegetation Indices (TBVIs) = 12246 unique indices for 157 useful Hyperion bands of data

$$HTBVI_{ij} = \frac{(R_j - R_i)}{(R_j + R_i)}$$

- **Hyperion**:
- **A. acquired over 400-2500 nm in 220 narrow-bands each of 10-nm wide bands. Of these there are 196 bands that are calibrated. These are: (i) bands 8 (427.55 nm) to 57 (925.85 nm) in the visible and near-infrared; and (ii) bands 79 (932.72 nm) to band 224 (2395.53 nm) in the short wave infrared.**
- **B. However, there was significant noise in the data over the 1206–1437 nm, 1790– 1992 nm, and 2365–2396 nm spectral ranges. When the Hyperion bands in this region were dropped, 157 useful bands remained.**

- **Spectroradiometer**:
- **A. acquired over 400-2500 nm in 2100 narrow-bands each of 1-nm wide. However, 1-nm wide data were aggregated to 10-nm wide to coincide with Hyperion bands.**
- **B. However, there was significant noise in the data over the 1350-1440 nm, 1790-1990 nm, and 2360-2500 nm spectral ranges. was seriously affected by atmospheric absorption and noise. The remaining good noise free data were in 400-1350 nm, and 1440-1790 nm, 1990-2360 nm.**

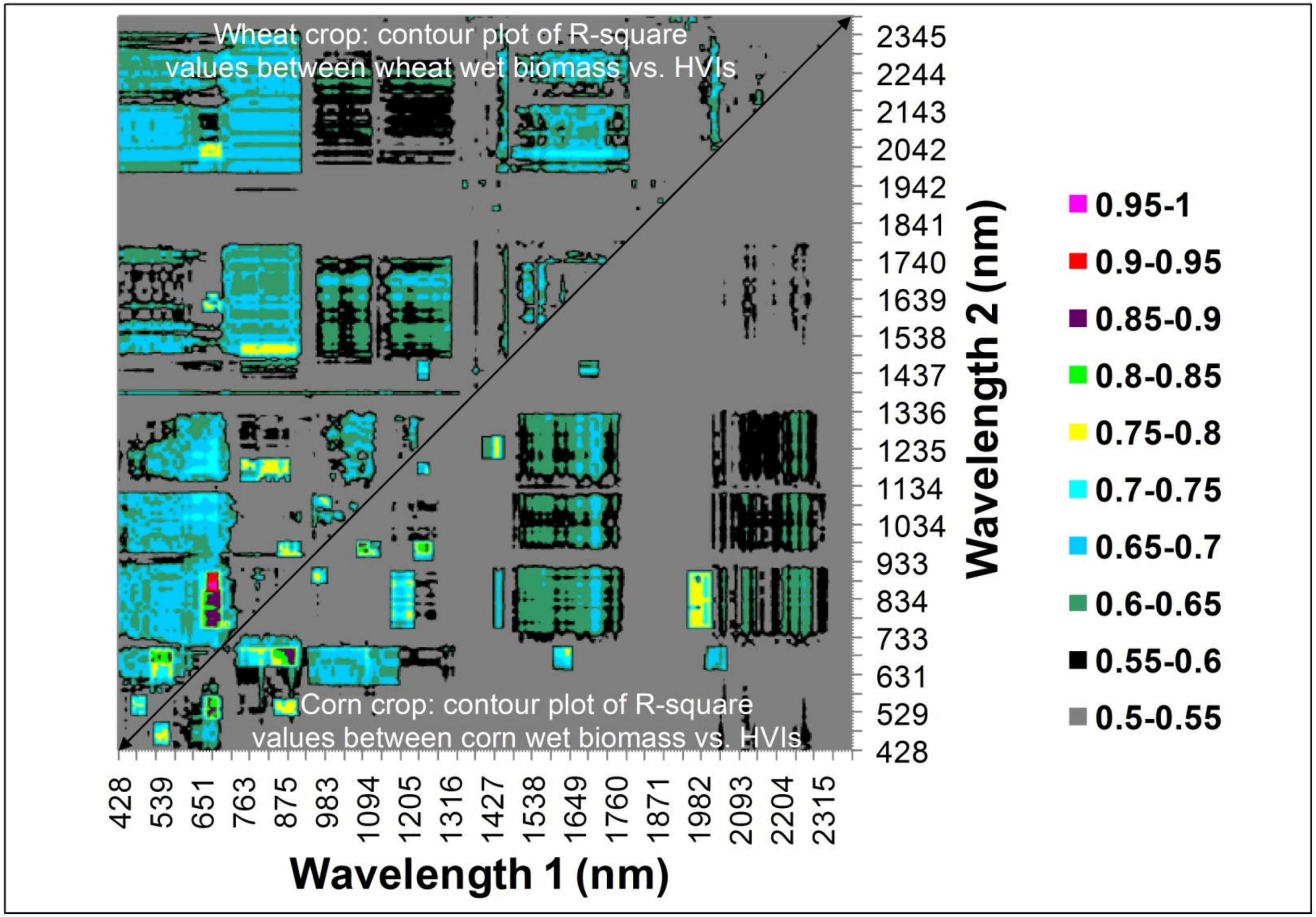
- **……..So, for both Hyperion and Spectroradiometer we had 157 useful bands, each of 10-nm wide, over the same spectral range.**

- **where, i,j = 1, N, with N=number of narrow-bands= 157 (each band of 1 nm-wide spread over 400 nm to 2500 nm), R=reflectance of narrow-bands.**

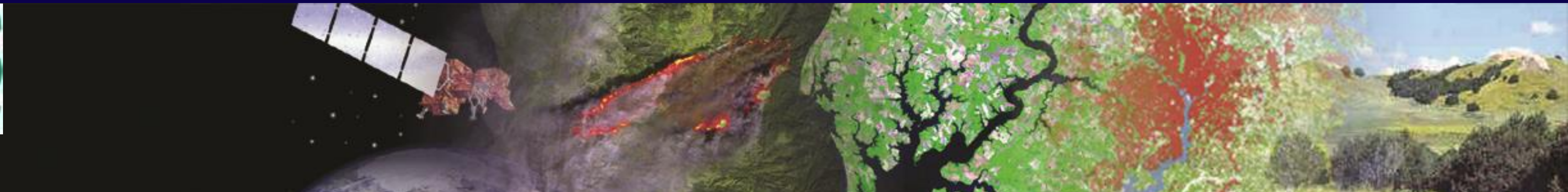
Model algorithm: two band NDVI algorithm in Statistical Analysis System (SAS). Computations are performed for all possible combinations of λ_1 (wavelength 1 = 157 bands) and λ_2 (wavelength 2 = 157 bands) - a total of 24,649 possible indices. It will suffice to calculate Narrow-waveband NDVI's on one side (either above or below) the diagonal of the 157 by 157 matrix as values on either side of the diagonal are the transpose of one another.

Hyperion Hyperspectral Data on Agricultural Crops from

Lambda versus Lambda R-square Contour plots of 2 Major Crops

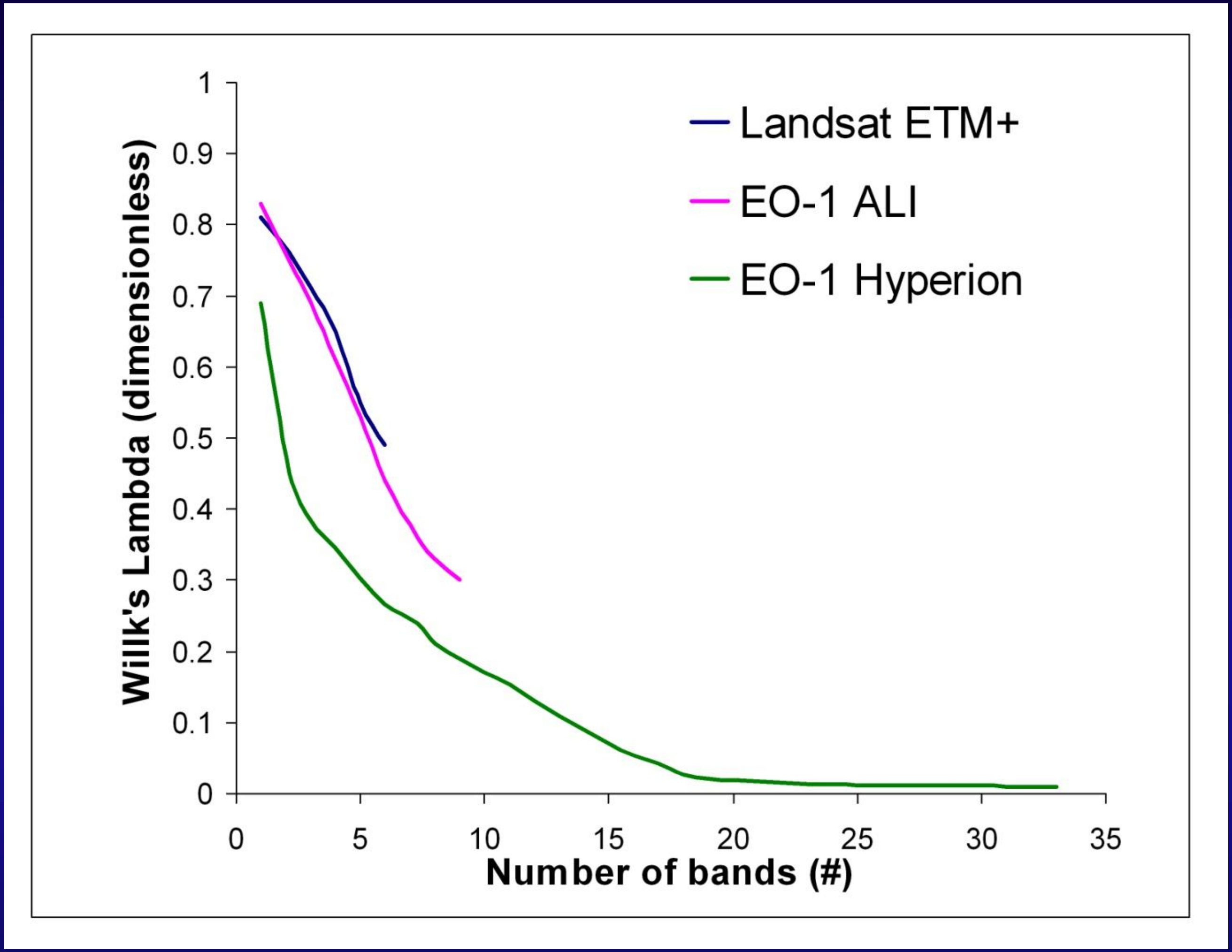


Contour plot of λ versus λ R^2- values for wavelength bands between two-band hyperspectral vegetation indices (HVIs) and wet biomass of wheat crop (above diagonal) and corn crop (below diagonal). The 242 Hyperion bands were reduced to 157 bands after eliminating uncalibrated bands and the bands in atmospheric window. HVIs were then computed using the 157 bands leading to 12,246 unique two-band normalized difference HVIs each of which were then related to biomass to obtain R-square values. These R^2-values were then plotted in a λ versus λ R^2-contour plot as shown above.



Hyperion Hyperspectral Narrowband Data versus Landsat ETM+ Broadband Data on Agricultural Crops

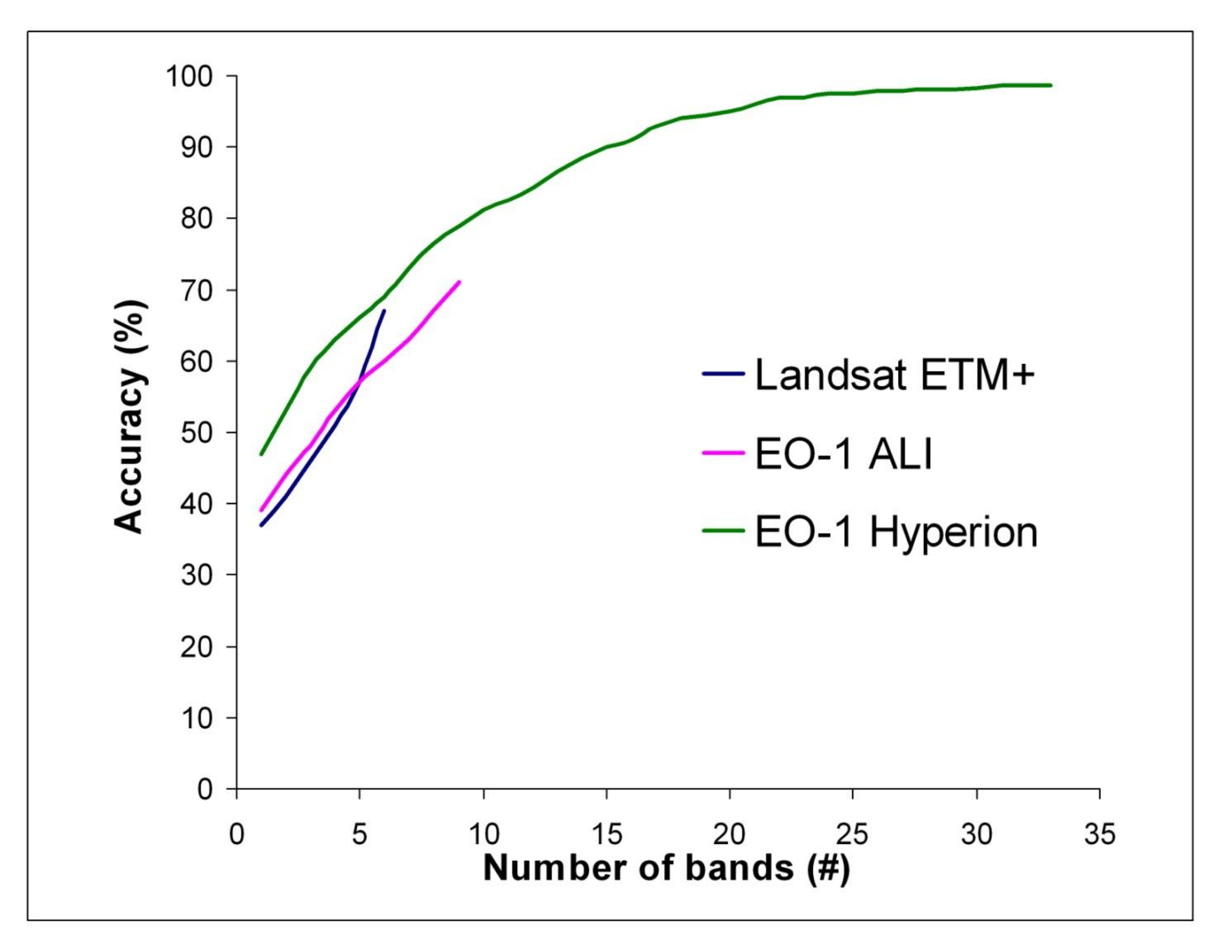
Wilk's Lambda of Broadband vs. Hyperspectral Narrowband data



Separating eight major crops of the world based on Wilks' Lambda stepwise discriminant analysis (SDA) method using: (a) broadband data of Landsat ETM+ and EO-1 ALI, and (b) hyperspectral narrowband (HNB) data of EO-1 Hyperion using some of the data of three study areas. Note: the smaller the Wilks' Lambda the greater the separability. A Wilks' Lambda of 1 means perfect separability. It took about 25 HNBs to achieve near perfect separability between eight crops.

Hyperion Hyperspectral Narrowband Data versus Landsat ETM+ Broadband Data on Agricultural Crops

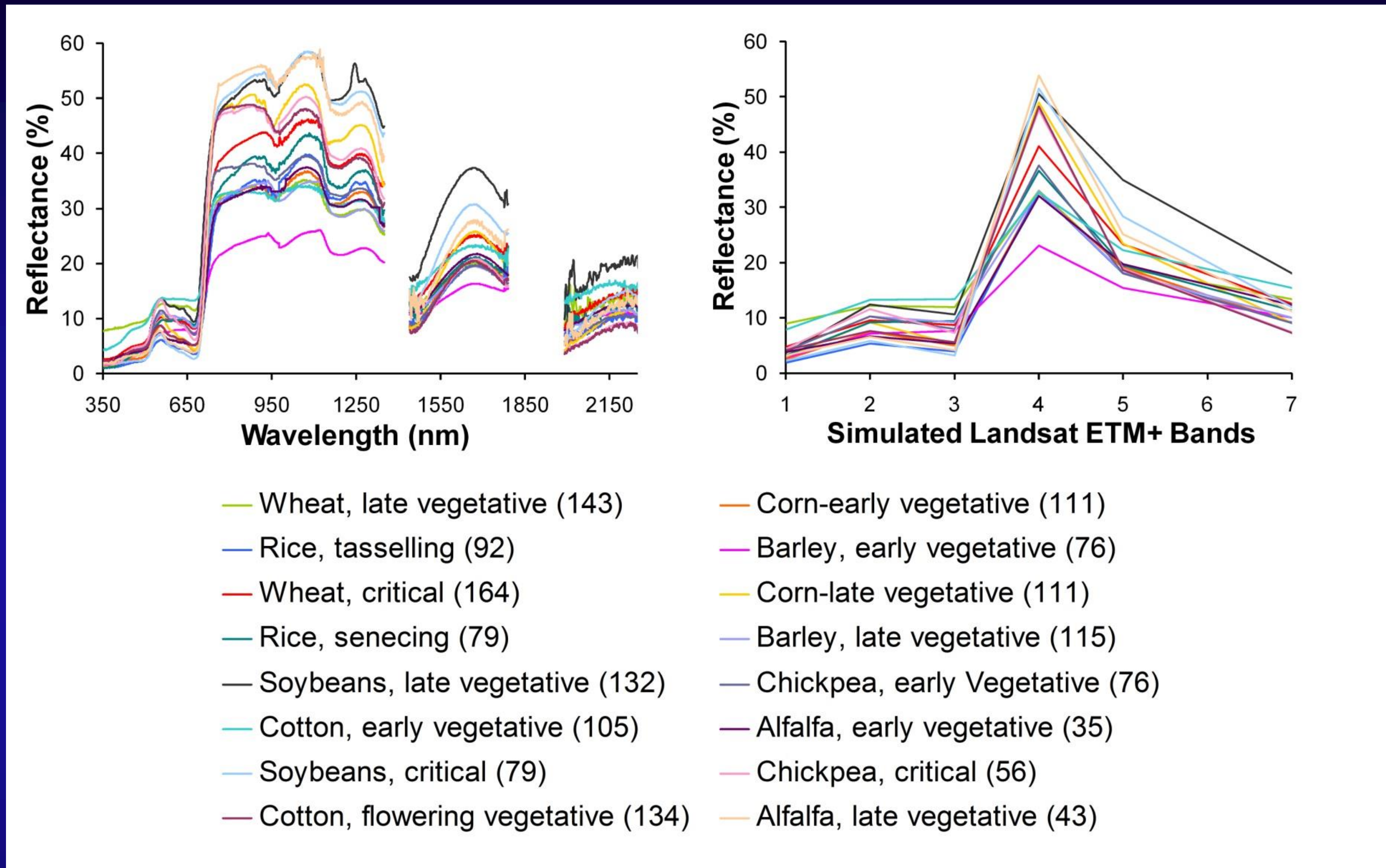
Wilk's Lambda of Broadband vs. Hyperspectral Narrowband data



Crop classification performance of hyperspectral narrowbands (HNBs) versus multispectral broadbands (MBBs). Overall accuracies in classifying five agricultural crops using simulated reflectance field spectra of Landsat ETM+ and EO-1 ALI broadband Landsat broadbands vs. Hyperion hyperspectral narrowbands. Overall accuracies attained using six non-thermal Landsat bands was about 60% whereas about 20 hyperspectral narrow bands provided about 90% overall accuracy. Beyond 20 bands, any increase in accuracy with increase in additional bands is very minor.

Hyperion Hyperspectral Narrowband Data versus Landsat ETM+ Broadband Data on Agricultural Crops

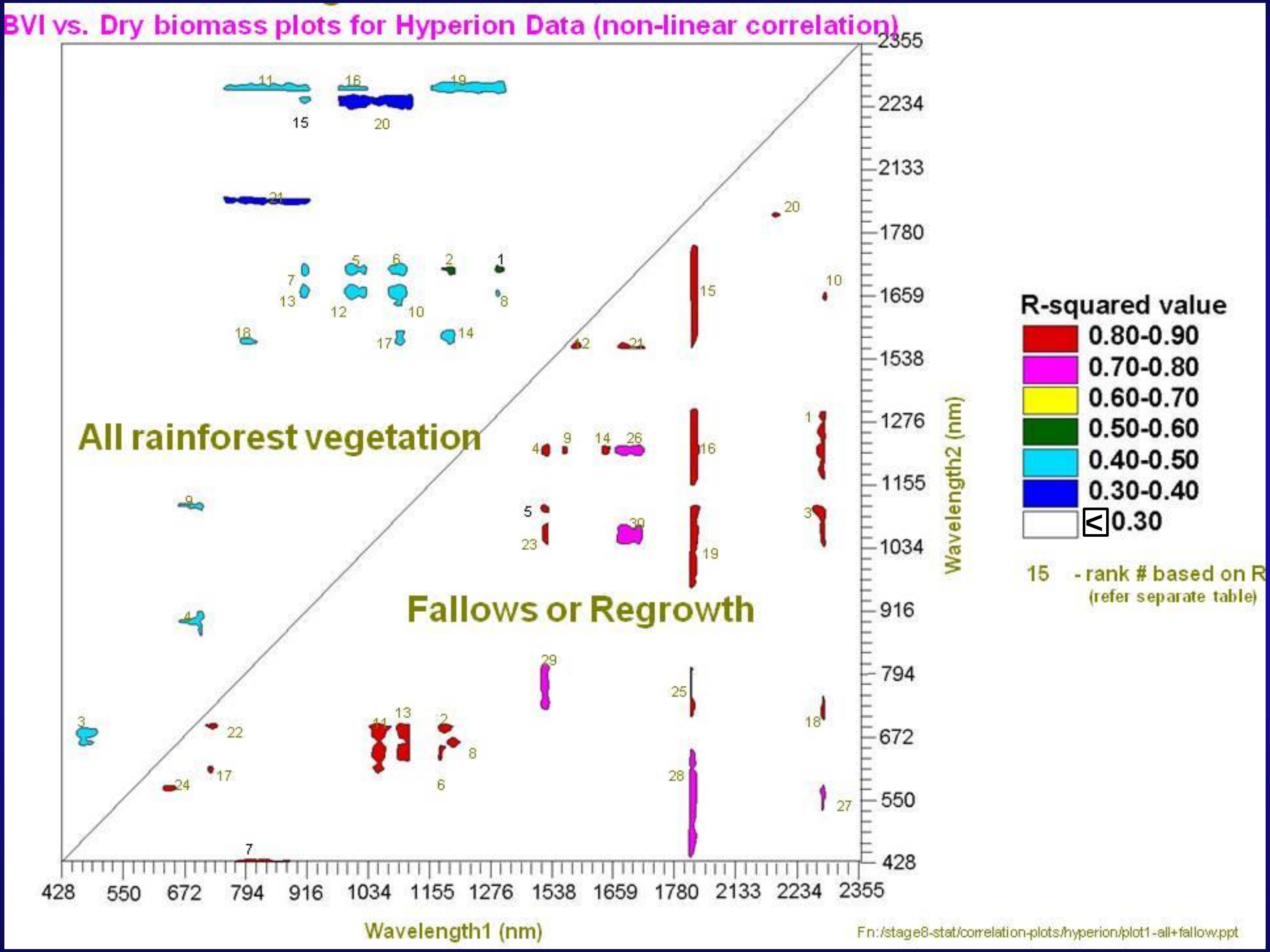
Hyperspectral Narrowband versus Simulated Landsat ETM+ broadband data



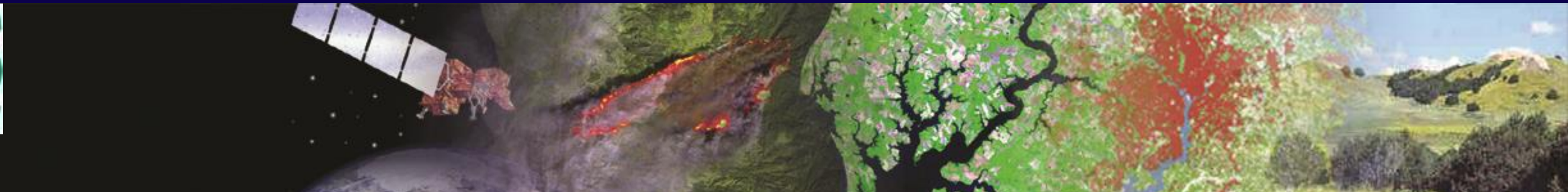
Original narrowband versus simulated broadband reflectance field spectra of leading world crops. The hyperspectral reflectance field spectra of eight leading crops, each at two distinct growth stages, are shown for narrowbands (left) and simulated for Landsat ETM+ broadbands (right). Note: sample size within brackets.

Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Lambda vs. Lambda R-square contour plot on non-linear biophysical quantity (e.g., biomass) vs. HTBVI models



Waveband combinations with greatest R^2 values Greater are ranked…….bandwidths can also be determined.



Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Hyperspectral Multi-band Vegetation Indices (HMBVIs)

$$HMBVI_i = \sum_{J=1}^{N} a_{ij} R_j$$

where, OMBVI = crop variable i, R = reflectance in bands j (j= 1 to N with N=157; N is number of narrow wavebands); a = the coefficient for reflectance in band j for i th variable.

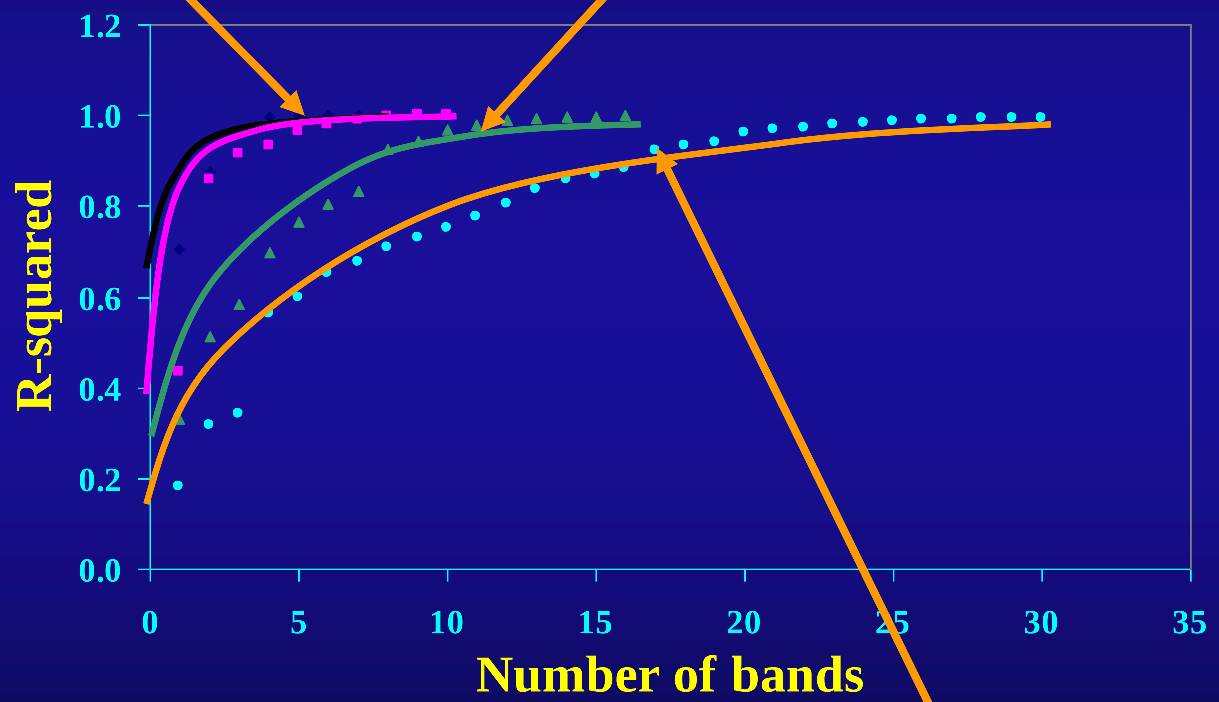
Model algorithm: MAXR procedure of SAS (SAS, 1997) is used in this study. The MAXR method begins by finding the variable (R_j) producing the highest coefficient of determination (R^2) value. Then another variable, the one that yields the greatest increase in R^2 value, is added…………….and so on…….so we will get the best 1-variable model, best 2-variable model, and so on to best n-variable model………………..when there is no significant increase in R^2-value when an additional variable is added, the model can stop.

Methods of Modeling Vegetation Characteristics using Hyperspectral Indices

Predicted biomass derived using MBVI's involving various narrowbands in African Rainforests

Note: Increase in R^2 values beyond 6 bands is negligible

Note: Increase in R^2 values beyond 11 bands is negligible

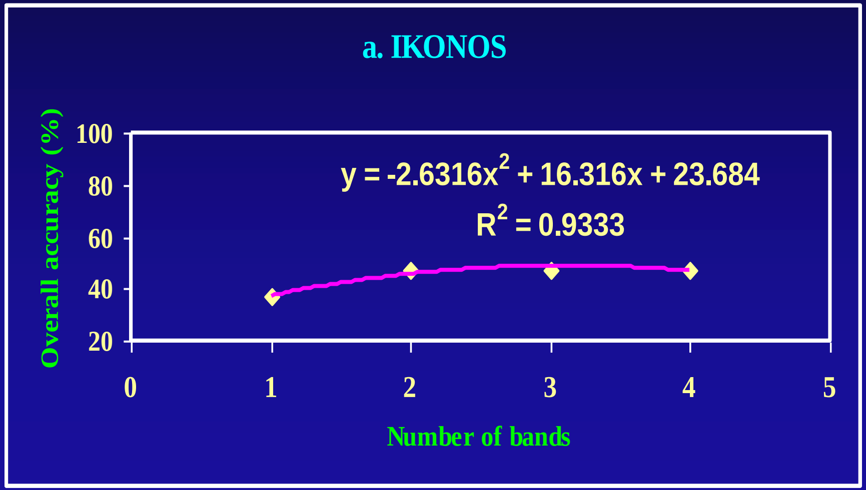


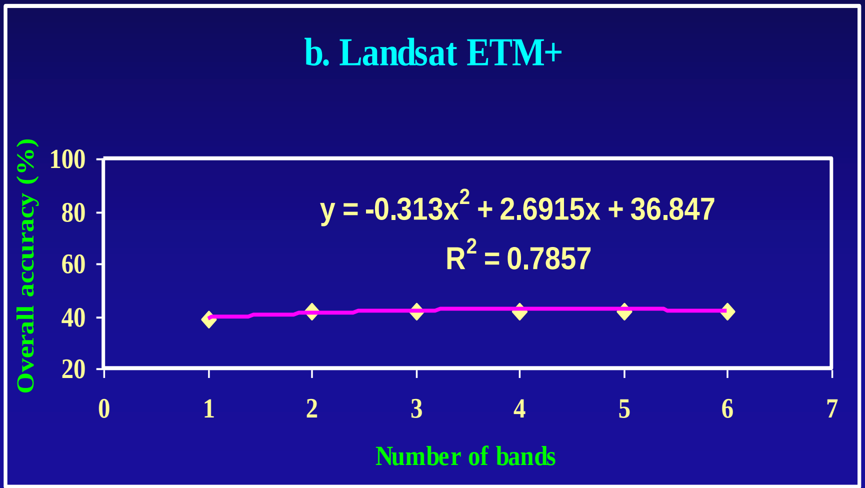
Note: Increase in R^2 values beyond 17 bands is negligible

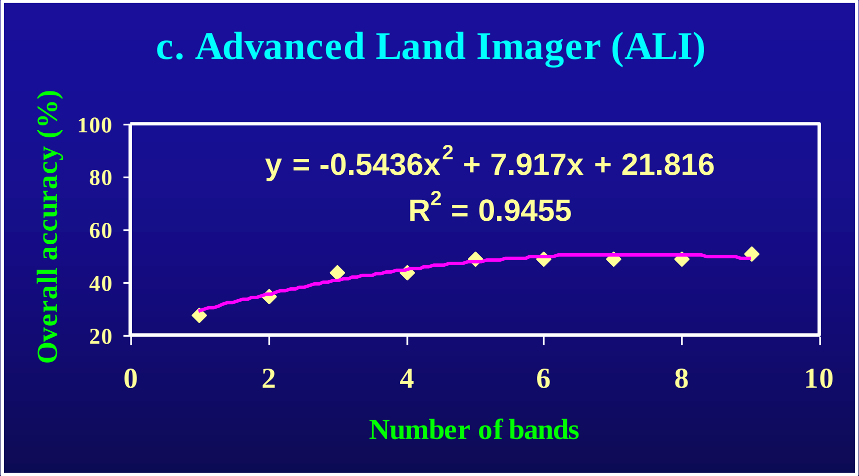
Methods of Classifying Vegetation Classes or Categories

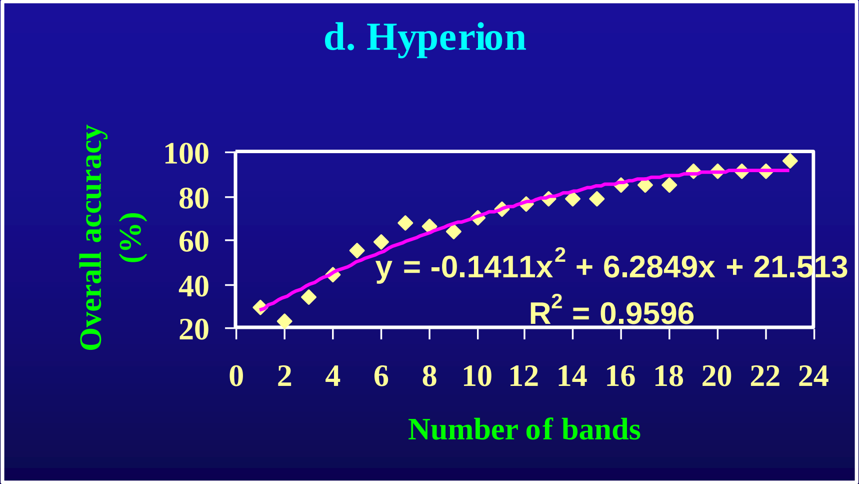
Discriminant Model or Classification Criterion (DM) to Test

How Well 12 different Vegetation are Discriminated using different Combinations of Broadbands vs. Narrowbands?









Hyperspectral Derivative Greenness Vegetation Indices (DGVIs)

First Order Hyperspectral Derivative Greenness Vegetation Index (HDGVI) (Elvidge and Chen, 1995): These indices are integrated across the (a) chlorophyll red edge:.626-795 nm, (b) Red-edge more appropriately 690-740 nm……and other wavelengths.

$$DGVI1 = \sum_{\lambda_1}^{\lambda_n} \frac{(\rho'(\lambda_i) - (\rho'(\lambda j)}{\Delta\lambda_I}$$

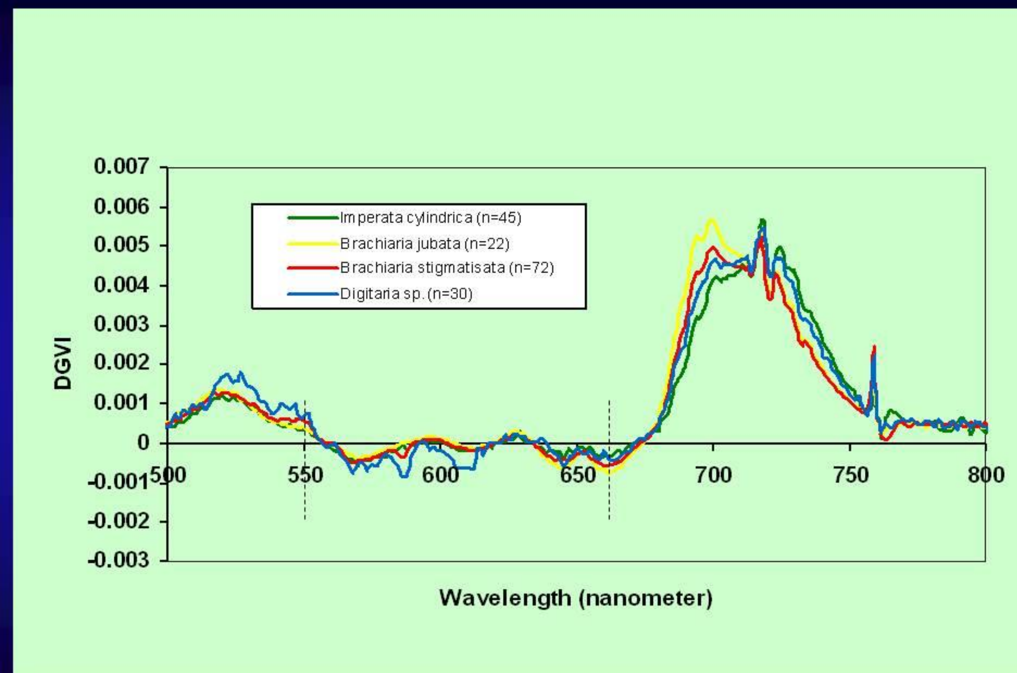
Where, I and j are band numbers,

λ = center of wavelength,

λ_1 = 0.626 μm,

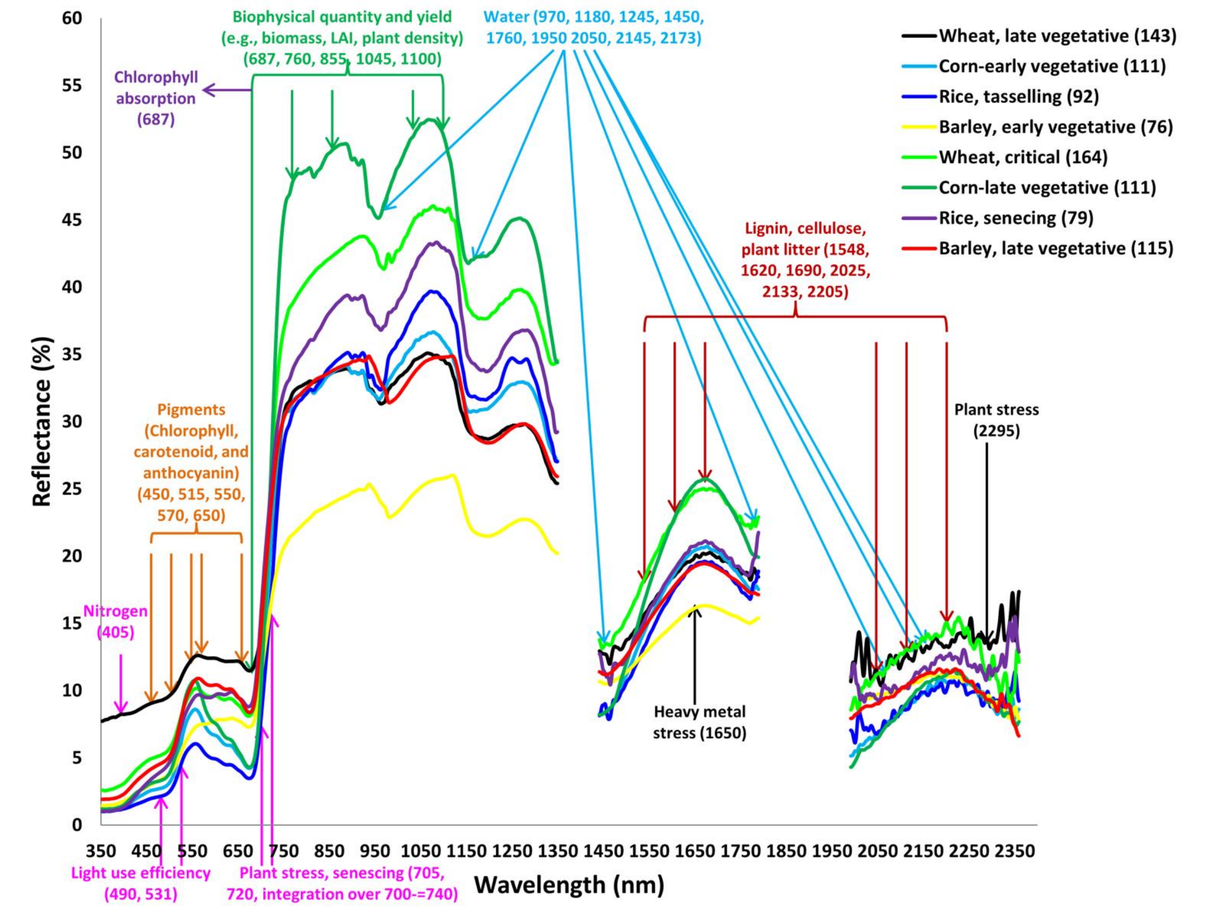
λ_n = 0.795 μm,

ρ' = first derivative reflectance.



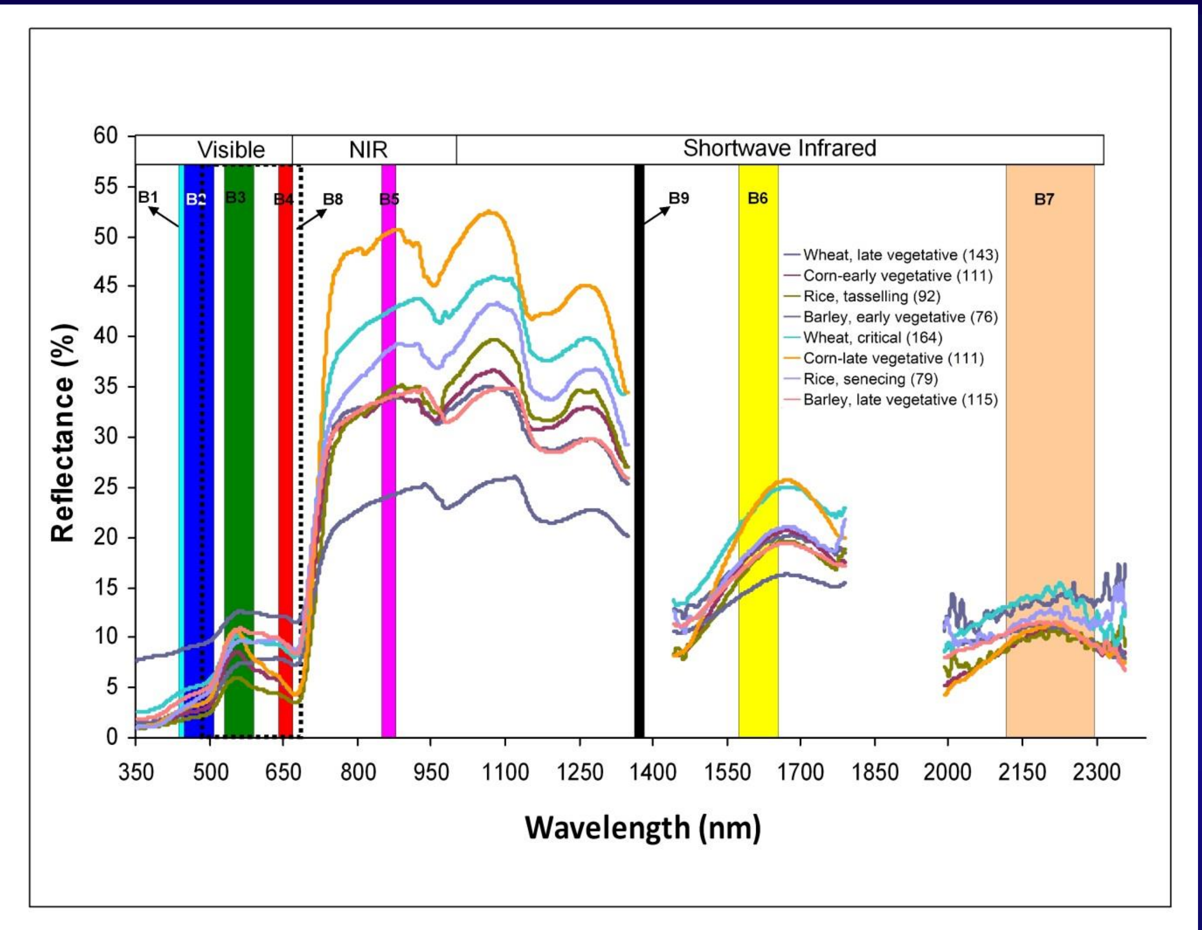
Note: HDGVIs are near-continuous narrow-band spectra integrated over certain wavelengths

Hyperspectral Narrowband Study of Agricultural Crops
Optimal Hyperspectral Narrowbands in Study of Agriculture

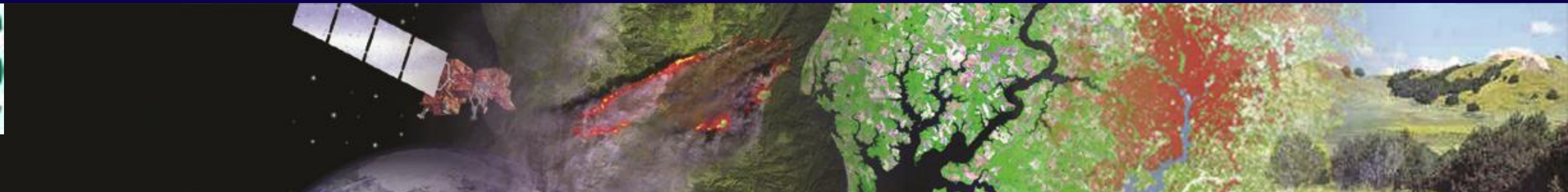


Optimal hyperspectral narrowbands (HNBs). Current state of knowledge on hyperspectral narrowbands (HNBs) for agricultural and vegetation studies (inferred from [8]). The whole spectral analysis (WSA) using contiguous bands allow for accurate retrieval of plant biophysical and biochemical quantities using methods like continuum removal. In contrast, studies on wide array of biophysical and biochemical variables, species types, crop types have established: (a) optimal HNBs band centers and band widths for vegetation/crop characterization, (b) targeted HVIs for specific modeling, mapping, and classifying vegetation/crop types or species and parameters such as biomass, LAI, plant water, plant stress, nitrogen, lignin, and pigments, and (c) redundant bands, leading to overcoming the Hughes Phenomenon. These studies support hyperspectral data characterization and applications from missions such as Hyperspectral Infrared Imager (HyspIRI) and Advanced Responsive Tactically Effective Military Imaging Spectrometer (ARTEMIS). Note: sample sizes shown within brackets of the figure legend refer to data used in this study.

Hyperspectral Narrowband Study of Agricultural Crops
Landsat 8 Band (except the 2 thermal) location

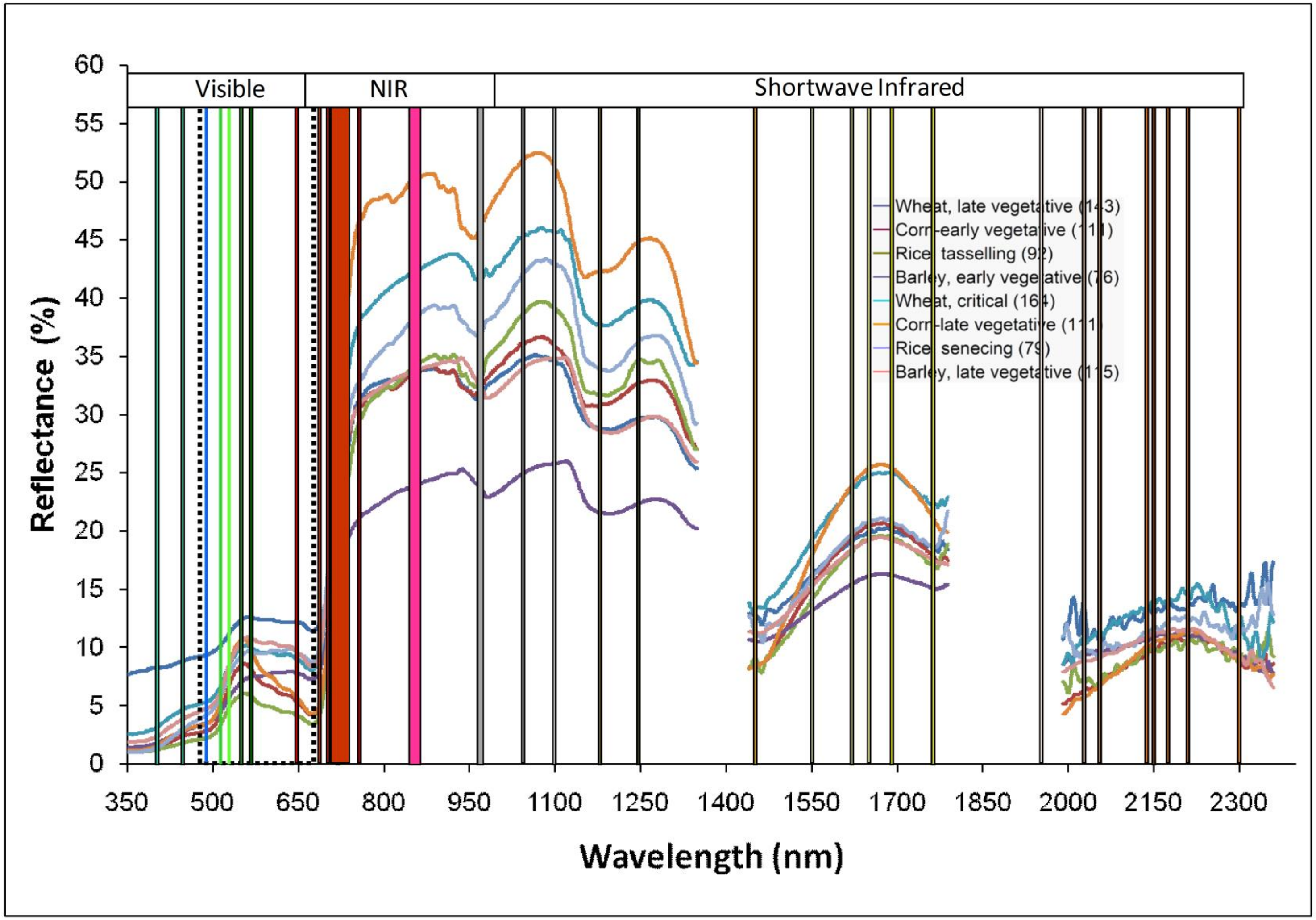


Optimal hyperspectral narrowbands (HNBs). Current state of knowledge on hyperspectral narrowbands (HNBs) for agricultural and vegetation studies (inferred from [8]). The whole spectral analysis (WSA) using contiguous bands allow for accurate retrieval of plant biophysical and biochemical quantities using methods like continuum removal. In contrast, studies on wide array of biophysical and biochemical variables, species types, crop types have established: (a) optimal HNBs band centers and band widths for vegetation/crop characterization, (b) targeted HVIs for specific modeling, mapping, and classifying vegetation/crop types or species and parameters such as biomass, LAI, plant water, plant stress, nitrogen, lignin, and pigments, and (c) redundant bands, leading to overcoming the Hughes Phenomenon. These studies support hyperspectral data characterization and applications from missions such as Hyperspectral Infrared Imager (HyspIRI) and Advanced Responsive Tactically Effective Military Imaging Spectrometer (ARTEMIS). Note: sample sizes shown within brackets of the figure legend refer to data used in this study.



Hyperspectral Narrowband Study of Agricultural Crops

33 Optimal Hyperspectral narrowbands (HNBs) in study of Agriculture and Vegetation



Hyperspectral Narrowband Study of Agricultural Crops

Best Hyperspectral Multiple Narrowband Combinations in Study of Agriculture

Table 3: The best 4, 6, 10, 15, and 20 band combinations of hyperspectral narrowbands (HNBs) for separating or discriminating crop types or classifying them.

Best 4 bands	550, 687, 855, 1180 nm
Best 6 bands	550, 687, 855, 1180, 1650, 2205 nm
Best 10 bands	550, 687, 720, 855, 970, 1180, 1245, 1450, 1650, 2205 nm
Best 15 bands	515, 550, 650, 687, 720, 760, 855, 970, 1110, 1180, 1245, 1450, 1650, 1950, 2205 nm
Best 20 bands	490, 515, 531, 550, 570, 650, 687, 720, 760, 855, 970, 1045, 1110, 1180, 1245, 1450, 1650, 1760, 1950, 2205 nm

Hyperspectral Remote Sensing (Imaging Spectroscopy) of Agricultural Crops

Recent (April, 2013) Publication

Thenkabail, P.S., Mariotto, I., Gumma, M.K.,, Middleton, E.M., Landis, and D.R., Huemmrich, F.K., 2013. Selection of hyperspectral narrowbands (HNBs) and composition of hyperspectral twoband vegetation indices (HVIs) for biophysical characterization and discrimination of crop types using field reflectance and Hyperion/EO-1 data. IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, Pp. 1-13, VOL. 6, NO. 2, APRIL 2013.

Selection of Hyperspectral Narrowbands (HNBs) and Composition of Hyperspectral Twoband Vegetation Indices (HVIs) for Biophysical Characterization and Discrimination of Crop Types Using Field Reflectance and Hyperion/EO-1 Data

Prasad S. Thenkabail, Isabella Mariotto, Murali Krishna Gumma, Elizabeth M. Middleton, David R. Landis, and K. Fred Huemmrich

***Abstract*—The overarching goal of this study was to establish optimal hyperspectral vegetation indices (HVIs) and hyperspectral narrowbands (HNBs) that best characterize, classify, model, and map the world's main agricultural crops. The primary objectives were: (1) crop biophysical modeling through HNBs and HVIs, (2) accuracy assessment of crop type discrimination using Wilks' Lambda through a discriminant model, and (3) meta-analysis to select optimal HNBs and HVIs for applications related to agriculture. The study was conducted using two Earth Observing One (EO-1) Hyperion scenes and other surface hyperspectral data for the eight leading worldwide crops (wheat, corn, rice, barley, soybeans, pulses, cotton, and alfalfa) that occupy ∼70% of all cropland areas globally. This study integrated data collected from multiple study areas in various agroecosystems of Africa, the Middle East, Central Asia, and India. Data were collected for the eight crop types in six distinct growth stages. These included (a) field spectroradiometer measurements (350–2500 nm) sampled at 1-nm discrete bandwidths, and (b) field biophysical variables (e.g., biomass, leaf area index) acquired to correspond with spectroradiometer measurements. The eight crops were described and classified using ∼20 HNBs. The accuracy of classifying these 8 crops using HNBs was around 95%, which was ∼25% better than the multi-spectral results possible from Landsat-7's Enhanced Thematic Mapper+ or EO-1's Advanced Land Imager. Further, based on this research and meta-analysis involving over 100 papers, the study established 33 optimal HNBs and an equal number of specific two-band normalized difference HVIs to best model and study specific biophysical and biochemical quantities of major agricultural crops of the world. Redundant bands identified in this study will help overcome the Hughes Phenomenon (or "the curse of high dimensionality") in hyperspectral data for a particular application (e.g., biophysical characterization of crops). The findings of this study will make a significant contribution to future hyperspectral missions such as NASA's HyspIRI.**

***Index Terms*—Hyperion, field reflectance, imaging spectroscopy, HyspIRI, biophysical parameters, hyperspectral vegetation indices, hyperspectral narrowbands, broadbands.**

I. Introduction and Rationale

NUMEROUS studies (e.g., [1], [2]) have shown that the Hyperion imaging spectrometer onboard the Earth Observing One (EO-1) satellite has provided significantly enhanced data over conventional multi-spectral remote sensing systems. Hyperspectral narrowbands (HNBs) and hyperspectral vegetation indices (HVIs) derived from EO-1 and field spectral measurements in the 400–2500 nm spectrum allow us to study very specific characteristics of agricultural crops. These include biomass, leaf area index (LAI), pigment content (e.g., chlorophyll, carotenoid, anthocyanin), stress (e.g., due to drought or disease), management properties (e.g., nitrogen application, tillage), and other biochemical properties (e.g., lignin, cellulose, plant residue) [23], [24]. The ability of hyperspectral data to significantly improve the characterization, discrimination, modeling, and mapping of crops and vegetation, when compared with broadband multispectral remote sensing, is well known [8]. This has led to improved and targeted modeling and mapping of specific agricultural characteristics, such as (a) biophysical and biochemical quantities [3]–[8], [13], (b) crop type/species discrimination [9]–[12], [15], (c) stress factors [14], [15], and (d) crop and water productivity, and energy balance [16]–[22]. These benefits will help us better understand a broad range of agricultural applications involving droughts [2], [3], food security [8]–[12], biodiversity [9], [11], and invasive species [9], [24]. Nevertheless, there are still significant knowledge gaps that require further research.

Contiguous bands of spectrometer data allow for accurate retrieval of plant biophysical and biochemical quantities using methods like continuum removal, first discussed by Clark and Roush in 1984 [25]–[28]. However, since information about agriculture is time sensitive, approximate analyses, quickly obtained using one or more HVIs may be more useful than

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science for a changing world

U.S. Geological Survey
U.S. Department of Interior

Concluding Thoughts

Hyperspectral (imaging Spectroscopy)

Knowledge Gain in Study of Vegetation

U.S. Geological Survey
U.S. Department of Interior

Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation
Knowledge Gain and Knowledge Gap After 40 years of Research

1. Hyperspectral narrowbands when compared with broadbands data can significantly improve in:

1.1. Discriminating\Separating vegetation and crop types and their species;

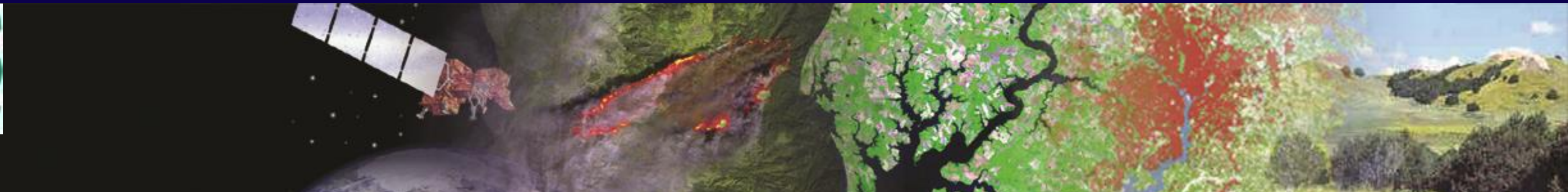
1.2. Explaining greater variability in modeling vegetation and crop biophysical, yield, and biochemical characteristics;

1.3. Increasing accuracies (reducing errors and uncertainties) in vegetation\land cover classification; and

1.4. Enabling the study of specific biophysical and biochemical properties from specific targeted portion of the spectrum.

2. About 33 narrowbands, in 400-2500 nm, provide optimal information in vegetation studies. These waveband centers are identified in this study. A nominal 3 to 5 nm wide bandwidth is recommended for all wavebands;

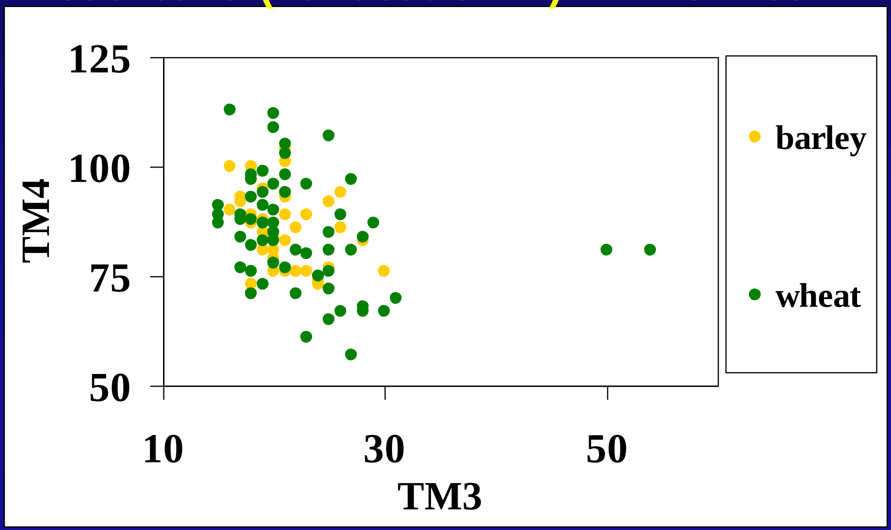
3. Advances in methods and approaches of hyperspectral data analysis in vegetation studies.



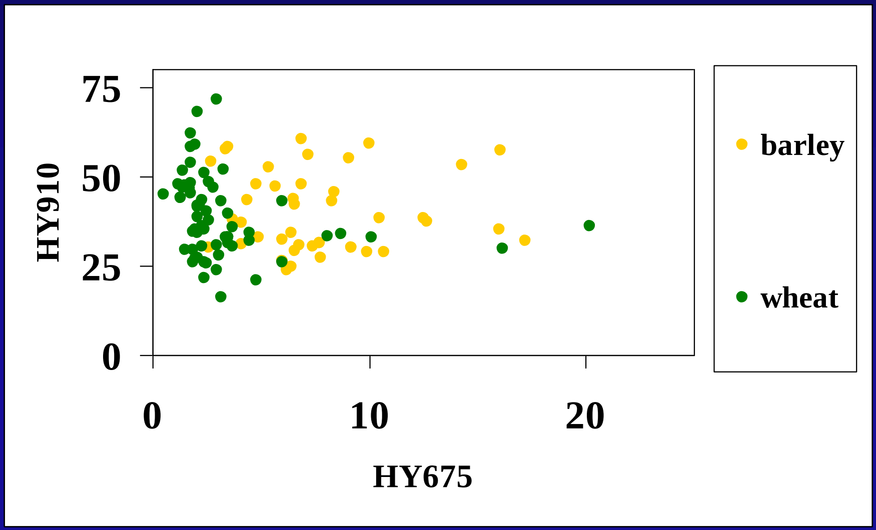
Discriminating\Separating Vegetation Types

Note: Distinct separation of vegetation or crop types or species using distinct narrowbands

Broad-band (Landsat-5 TM) NIR vs. Red

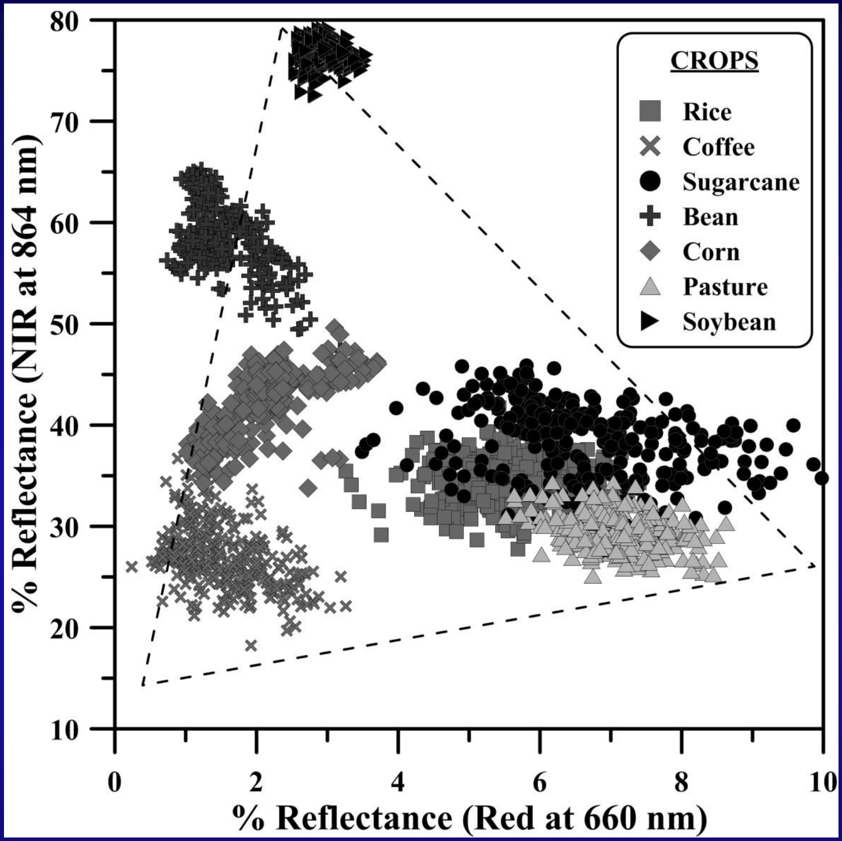


Narrow-band NIR vs. Red

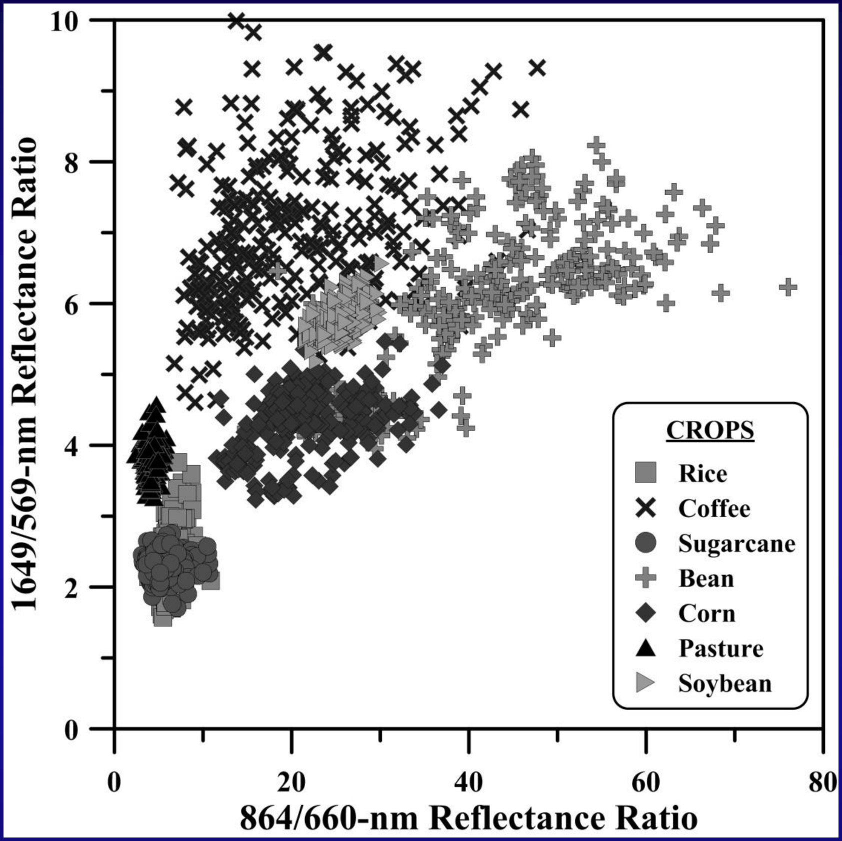


Numerous narrow-bands provide unique opportunity to discriminate different crops and vegetation.

Separating Agricultural Crop Classes or Categories



Relationships between red and near infrared (NIR) Hyperion bands for the studied crop types. The triangle is discussed in the text.

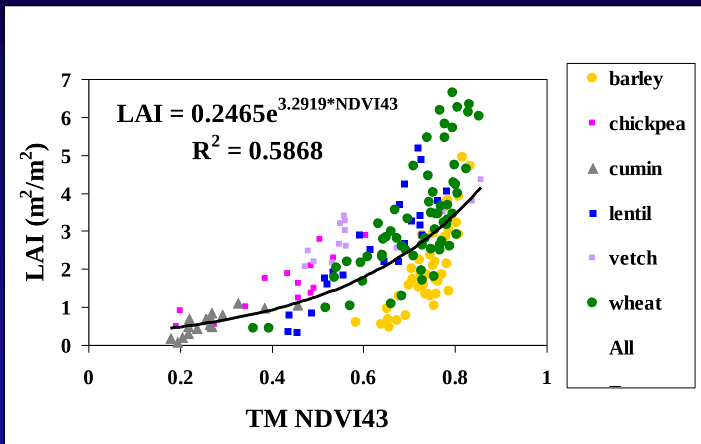


Variation in NIR-1/red and SWIR-1/green reflectance ratios for the crop types under study.

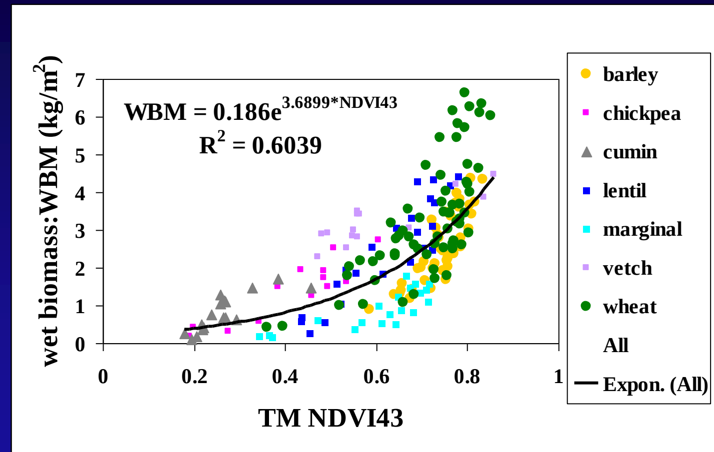
Note: see chapter 17

Hyperspectral Remote Sensing of Vegetation: Knowledge Gain and Knowledge Gap After 40 years of Research

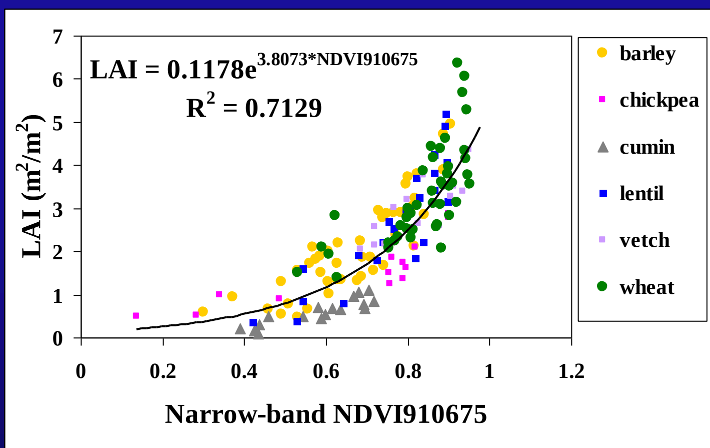
Improved Biophysical and Biochemical Modeling



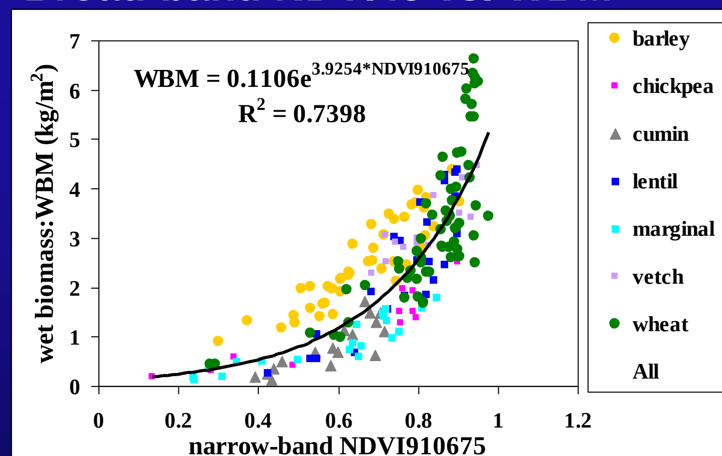
Broad-band NDVI43 vs. LAI



Broad-band NDVI43 vs. WBM



Narrow-band NDVI43 vs. LAI



Narrow-band NDVI43 vs. WBM

Note: Improved models of vegetation biophysical and biochemical variables: The combination of wavebands in Table 28.1 or HVIs derived from them provide us with significantly improved models of vegetation variables such as biomass, LAI, net primary productivity, leaf nitrogen, chlorophyll, carotenoids, and anthocyanins. For example, stepwise linear regression with a dependent plant variable (e.g., LAI, Biomass, nitrogen) and a combination of "N" independent variables (e.g., chosen by the model from Table 28.1) establish a combination of wavebands that best model a plant variable

Narrow-band indices explain about 13 percent greater variability in modeling crop variables.

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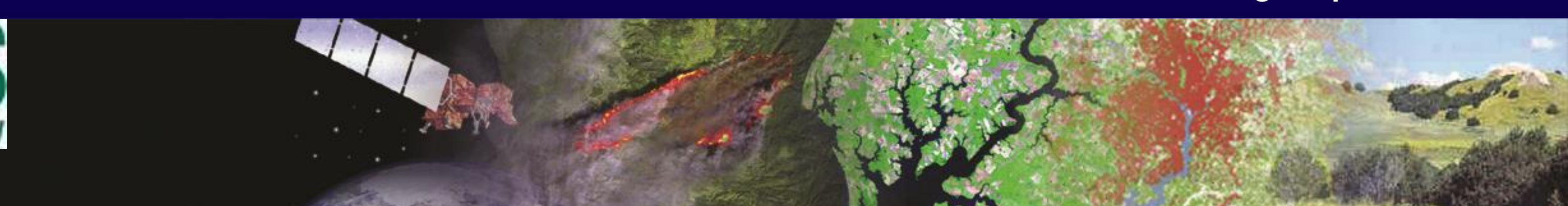
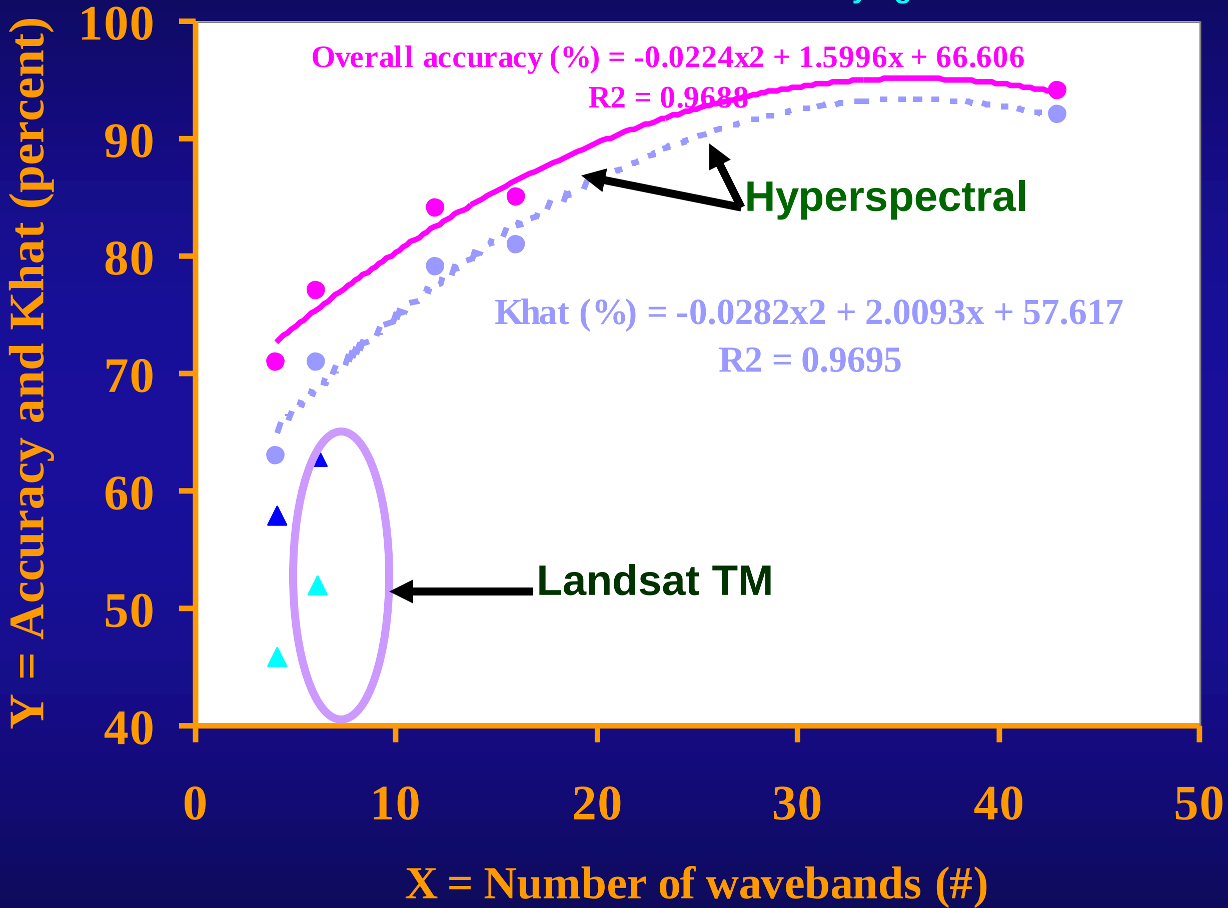
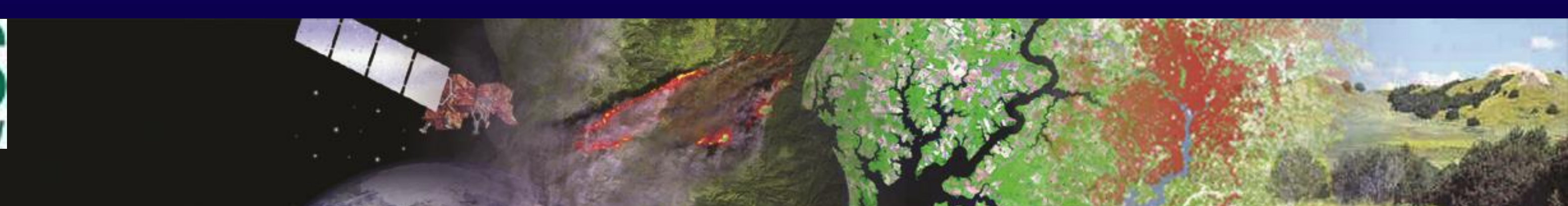


Improved Classification Accuracies (and reduced Errors and uncertainties)

Note: Overall Accuracies and K_{hat} Increase by about 30 % using 20 narrow-bands compared 6 non-thermal TM broad-bands in classifying 12 classes

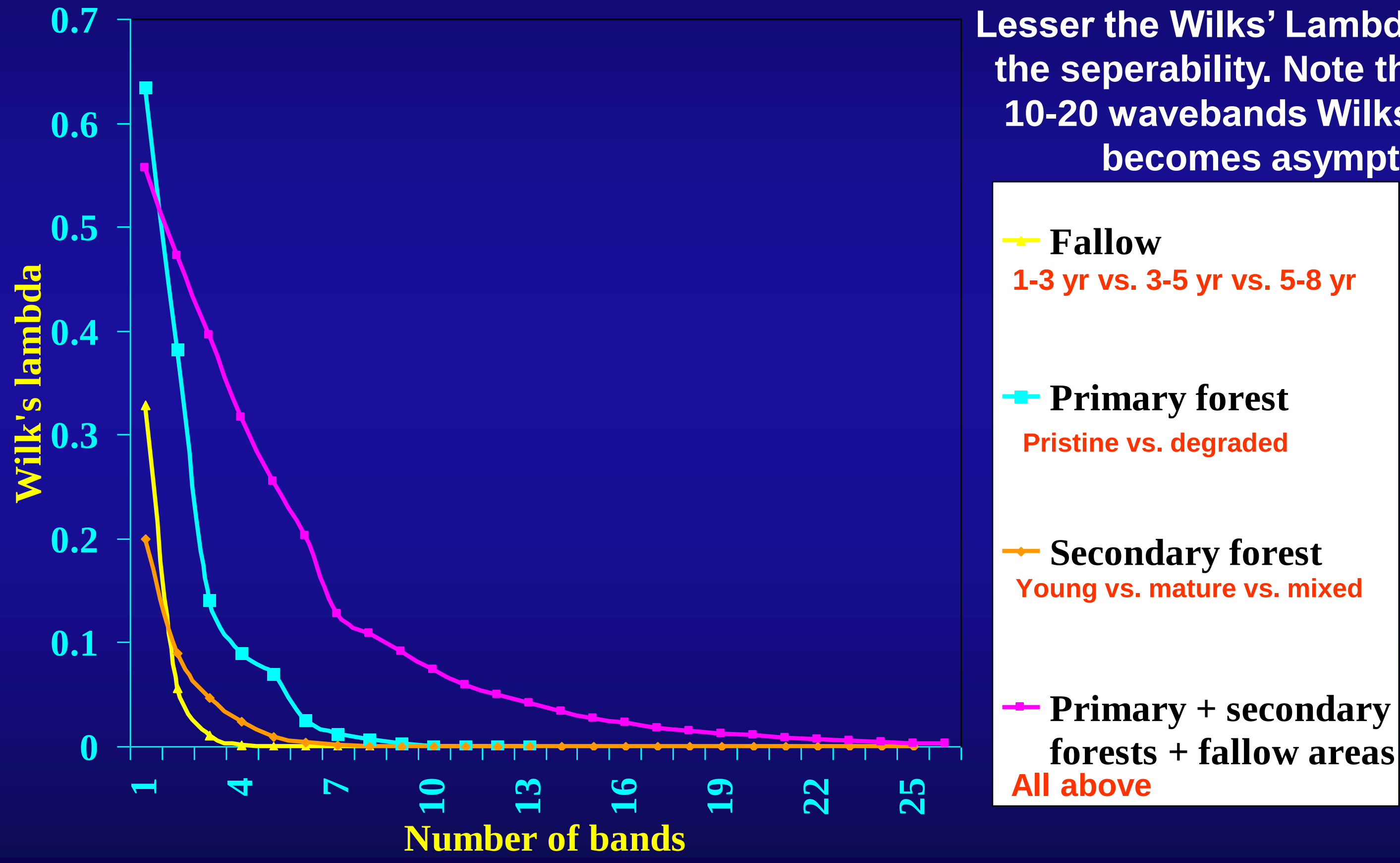


Note: **Improved accuracies in vegetation type or species classification: Combination of these wavebands in Table 28.1 help provide significantly improved accuracies (10-30 %) in classifying vegetation types or species types compared to broadband data;**



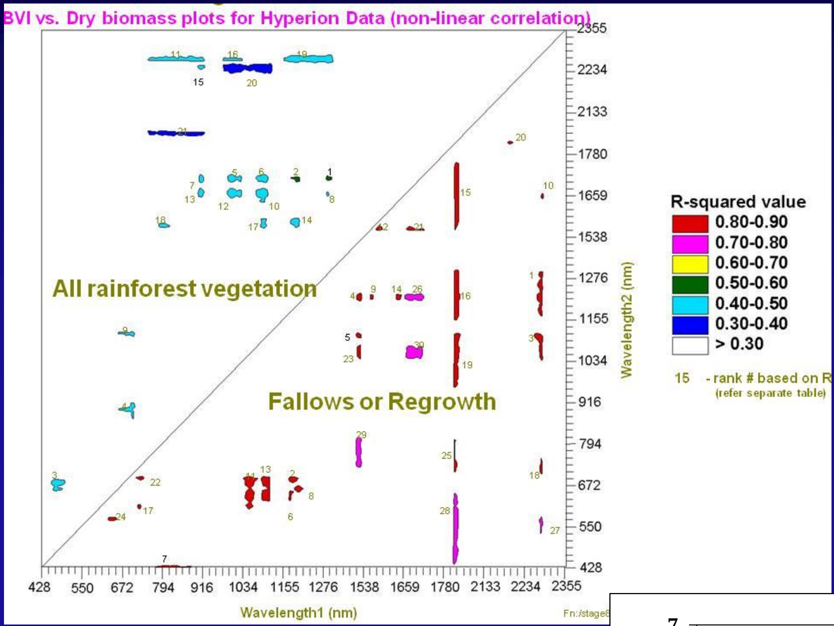
Improved Classification Accuracies (and reduced Errors and uncertainties)

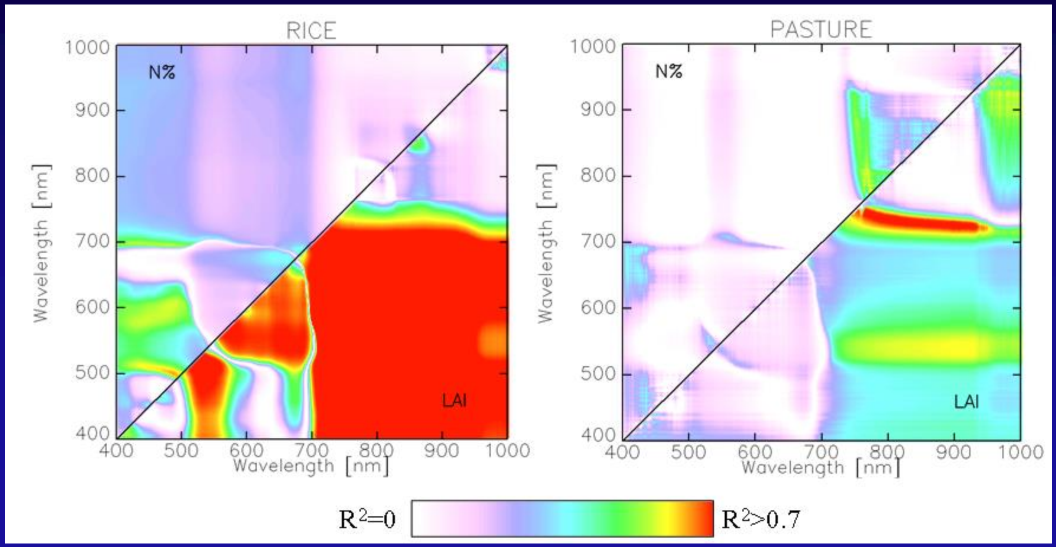
Stepwise Discriminant Analysis (SDA)- Wilks' Lambda to Test : How Well Different Forest Vegetation are Discriminated from One Another

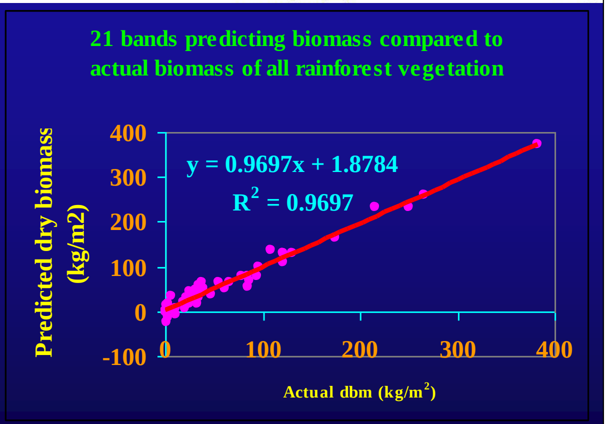


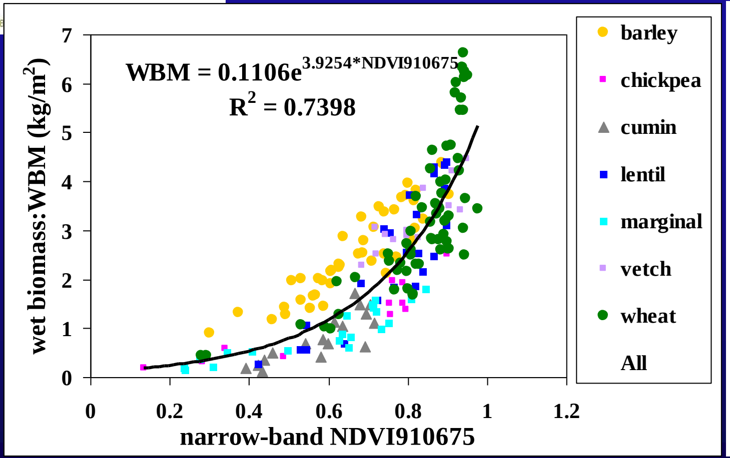
Lesser the Wilks' Lambda greater is the seperability. Note that beyond 10-20 wavebands Wilks' Lambda becomes asymptotic.

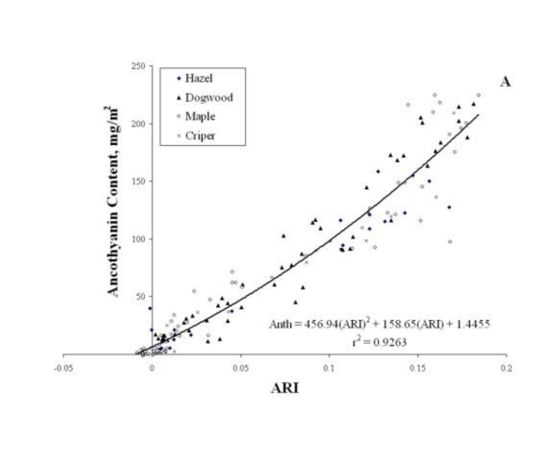
Improved Biophysical and Biochemical Modeling





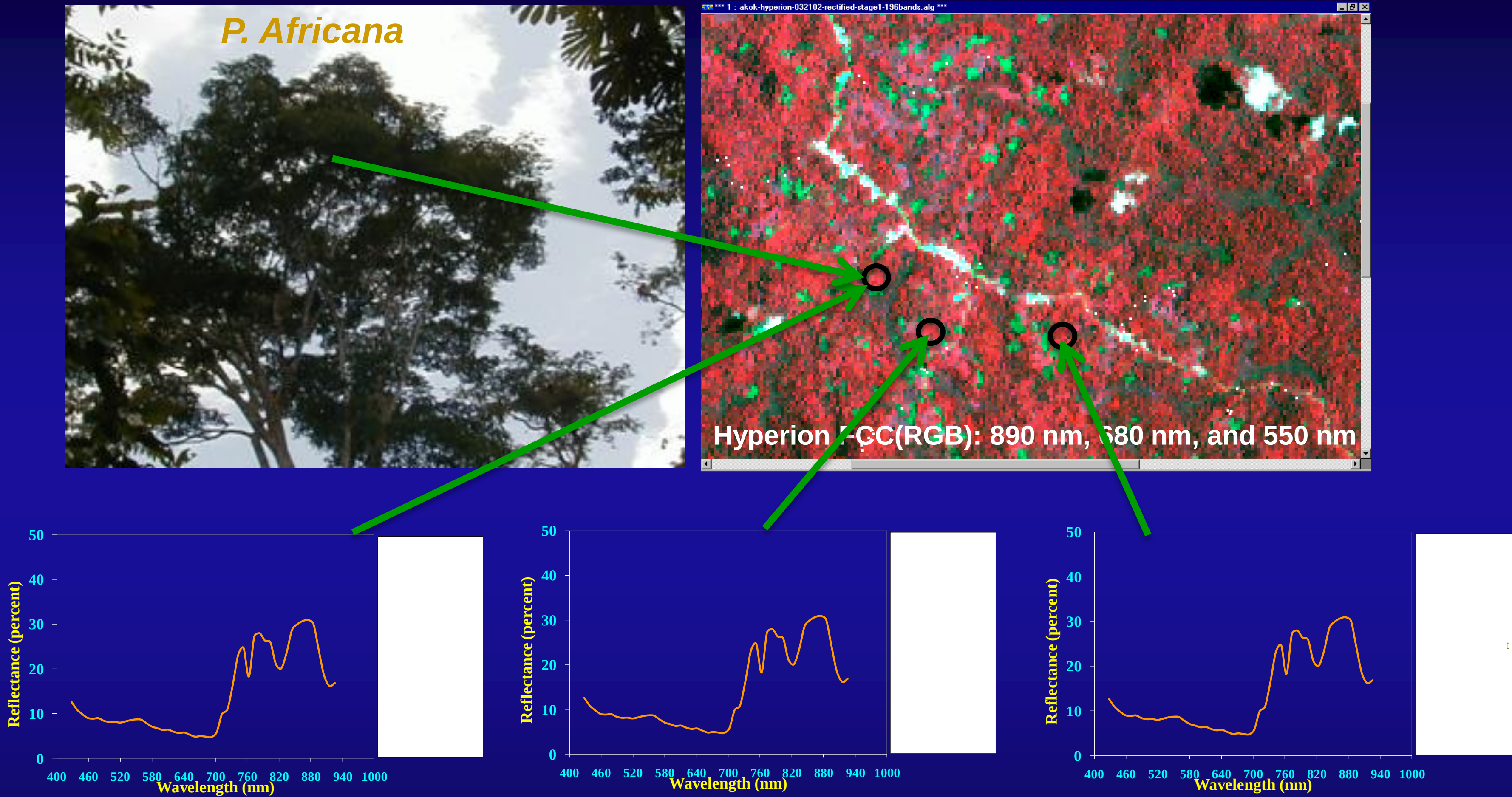






Hyperspectral Remote Sensing of Vegetation: Knowledge Gain and Knowledge Gap After 40 years of Research

Spectral Signature Data Bank of Vegetation Species (e.g., P. Africana)



Hyperspectral (Imaging Spectroscopy) Narrowband Study of Agricultural Crops
Optimal Hyperspectral Narrowbands (HNBs) and Vegetation Indices (HVIs)

Thenkabail, P.S., Mariotto, I., Gumma, M.K.,, Middleton, E.M., Landis, and D.R., Huemmrich, F.K., 2013. Selection of hyperspectral narrowbands (HNBs) and composition of hyperspectral twoband vegetation indices (HVIs) for biophysical characterization and discrimination of crop types using field reflectance and Hyperion/EO-1 data. IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, Pp. 1-13, VOL. 6, NO. 2, APRIL 2013.

TABLE IV

OPTIMAL HYPERSPECTRAL NARROWBANDS (HNBS) AND VEGETATION INDICES (HVIS) TO STUDY MAJOR WORLD CROPS BASED ON THE λ VERSUS λ R^2-PLOTS INVOLVING HNBS OR HVIS WITH BIOPHYSICAL PARAMETER BASED ON THIS STUDY AND META-ANALYSIS. (ADOPTED FROM [8])

Sl. numbe #	Waveband centers λ nm	Waveband widths Δλ nm	Hyperspectral Vegetation Indices (HVIs) normalized HVIs*** dimensionless
A. Blue bands			**1. Biophysical indices ((biomass, LAI, plant density, yield)**
1	405	5	HVI REDND1=(855-687)/(855+687) [27,30,31]
2	450	5	HVI REDND2=(855-650)/(855+650) [25,30,31]
3	490	5	HVI REDND3=(760-687)/(760+687) [25,30,31]
B. Green bands			HVI REDND4=(760-650)/(760+650) [25,30,31]
4	515	5	HVI GREENND1=(550-687)/(550+687) [4,5,13]
5	531	1	HVI GREENND2=(550-650)/(550+650) [3,13,25]
6	550	5	HVI FNIRND1=(1045-687)/(1045+687) [27,29,33]
7	570	5	HVI FNIRND2=(1045-650)/(1045+650) [27,29,33]
C. Red bands			HVI FNIRND3=(1245-687)/(1245+687) [7,10,30]
8	650	5	HVI FNIRND4=(1245-650)/(1245+650) [7,10,27]
9	687	5	HVI SWIRND1=(1650-687)/(1650+687) [7,10,31]
D. Red-edge bands			HVI SWIRND2=(1650-650)/(1650+650) [7,10,31]
10	705	5	HVI SWIRND3=(2205-687)/(2205+687) [14,24,30]
11	720	5	HVI SWIRND4=(2205-650)/(2205+650) [14,30,31]
12	700-740	700-740 (integrate)	**2. Biochemical indices ((carotenoids, anthocyanins, chlorophyll)**
E. Near infrared (NIR) bands			HVI Car1=(550-515)/(550+515) [4,5,10]
13	760	5	HVI Car2=(550-687)/(550+687) [27,30,31]
14	855	20	HVI Antho1=(720-550)/(720+550) [7,11,27]
15	970	10	HVI Antho2=(550-515)/(550+515) [10,23]
16	1045	5	HVI Antho3=(855-550)/(855+550) [4,5,14]
E. Far near infrared (FNIR) bands			HVI Antho4=(550-687)/(550+687) [4,5,14]
17	1100	5	HVI Chl1=(855-720)/(855+720) [27,30,31]
18	1180	5	**3. Plant stress indices**
19	1245	5	HVI REDEDGE1=(760-720) [7,25,30]
F. Early short-wave infrared (ESWIR) bands			HVI REDEDGE2=(760-720)/(760-720) [24,25,31]
20	1450	5	HVI REDEDGE3=first-order integrated spectra over 700 to 740 [25,30,31]
21	1548	5	**4. Plant Water and moisture indices**
22	1620	5	HVI WATER1=(855-970)/(855+970) [24,25,30]
23	1650	5	HVI WATER2=(1100-970)/(1100+970) [3,7,27]
24	1690	5	HVI WATER3=(1100-1180)/(1100+1180) [3,27,30]
25	1760	5	HVI WATER4=(1245-1180)/(1245+1100) [24,25,29]
G. Far short-wave infrared (FSWIR) bands			HVI WATER5=(1650-1450)/(1650+1450) [14,23,27]
26	1950	5	HVI WATER6=(2205-1450)/(2205+1450) [14,25,30]
27	2025	5	HVI WATER7=(2205-1950)/(2205+1950) [3,24,29]
28	2050	5	**5. Light use efficiency (LUE)**
29	2133	5	HVI LUE1=(570-531)/(570+531) [6,27,30]
30	2145	5	**6. Legnin, Cellulose, Residue index**
31	2173	5	HVI LCR1=(2205-2025)/(2205+2025) [14,27,30]
32	2205	5	
33	2295	5	

*** = For broader physical/biological understanding of these indices refer to the references cited next to each index or to various chapters in the book [8].

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Hyperspectral (Imaging Spectroscopy) Narrowband Study of Vegetation

Hyperspectral Narrowbands in Study of Vegetation (1 of 2)

A. Blue bands		
1	405	Nitrogen, Senescing
2	450	Chlorophyll, carotenoids, senescing
3	490	Carotenoid, Light use efficiency (LUE), Stress in vegetation
B. Green bands		
4	515	Pigments (Carotenoid, Chlorophyll, anthocyanins), Nitrogen, Vigor
5	531	Light use efficiency (LUE), Xanophyll cycle, Stress in vegetation, pest and disease
6	550	Anthocyanins, Chlorophyll, LAI, Nitrogen, light use efficiency
7	570	Pigments (Anthrocyanins, Chlorophyll), Nitrogen
C. Red bands		
8	650	Pigment, nitrogen
9	687	Biophysical quantities, chlorophyll, solar induced chlorophyll Floroscense
D. Red-edge bands		
10	705	Stress in vegetation detected in red-edge, stress, drought
11	720	Stress in vegetation detected in red-edge, stress, drought
12	700-740	Chlorophyll, senescing, stress, drought
E. Near infrared (NIR) bands		
13	760	Biomass, LAI, Solar-induced passive emissions
14	855	Biophysical\biochemical quantities, Heavy metal stress
15	970	Water absorption band
16	1045	Biophysical and biochemical quantities

Note:

* = wavebands were selected based on research and discussions in the chapters;

** = when there were close wavebands (e.g., 960 nm, 970 nm), only one waveband (e.g., 970 nm) was selected based on overwhelming eveidence as reported in various chapters. This would avoid redundancy.

*** = a nominal 5 nm waveband width can be considered optimal for obtaining best results with above wavebands as band centers. So, for 970 nm waveband center, we can have a band of range of 968-972 nm.

**** = The above wavebands can be considered as optimal for studying vehetation. Adding more waveband will only add to redundancy. Vegetation indices can be computed using above wavebands.

***** = 33 wavebands lead to a matrix of 33 x 33 = 1089 two band vehetation indices (TBVIs). Given that the indices above the diagonal and below diagonal replicate and indices along diagonal are redundant, there are 5

Note 1: Overcomes data redundancy and yet retains optimal solution.

Note 2: for each band, a bandwidth of 3 nm will be ideal, 5 nm maximum to capture the best characteristics of vegetation.

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Hyperspectral (Imaging Spectroscopy) Narrowband Study of Vegetation

Hyperspectral Narrowbands in Study of Vegetation (2 of 2)

E. Far near infrared (FNIR) bands		
17	1100	Biophysical quantities
18	1180	Water absorption band
19	1245	Water sensitivity
F. Early short-wave infrared (ESWIR) bands		
20	1450	Water absorption band
21	1548	Lignin, cellulose
22	1620	Lignin, cellulose
23	1650	Heavy metal stress, Moisture sensitivity
24	1690	Lignin, cellulose, sugar, starch, protein
25	1760	Water absorption band, senescence, lignin, cellulose
G. Far short-wave infrared (FSWIR) bands		
26	1950	Water absorption band
27	2025	Litter (plant litter), lignin, cellulose
28	2050	Water absorption band
29	2133	Litter (plant litter), lignin, cellulose
30	2145	Water absorption band
31	2173	Water absorption band
32	2205	Litter, lignin, cellulose, sugar, startch, protein; Heavy metal stress
33	2295	Stress and soil iron content

Note 1: Overcomes data redundancy and yet retains optimal solution.

Note 2: for each band, a bandwidth of 3 nm will be ideal, 5 nm maximum to capture the best characteristics of vegetation.

Note:

* = wavebands were selected based on research and discussions in the chapters;

** = when there were close wavebands (e.g., 960 nm, 970 nm), only one waveband (e.g., 970 nm) was selected based on overwhelming eveidence as reported in various chapters. This would avoid redundancy.

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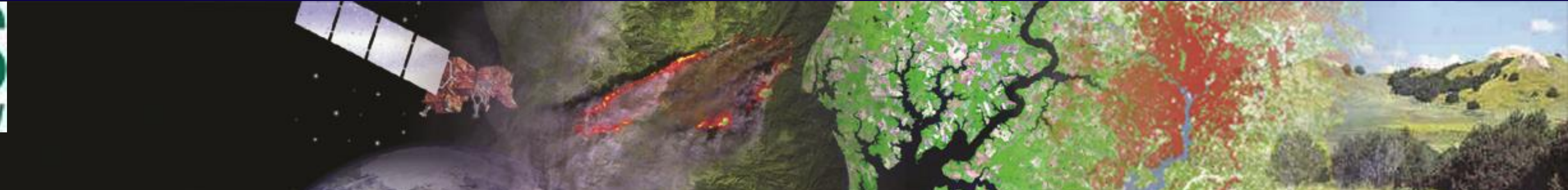
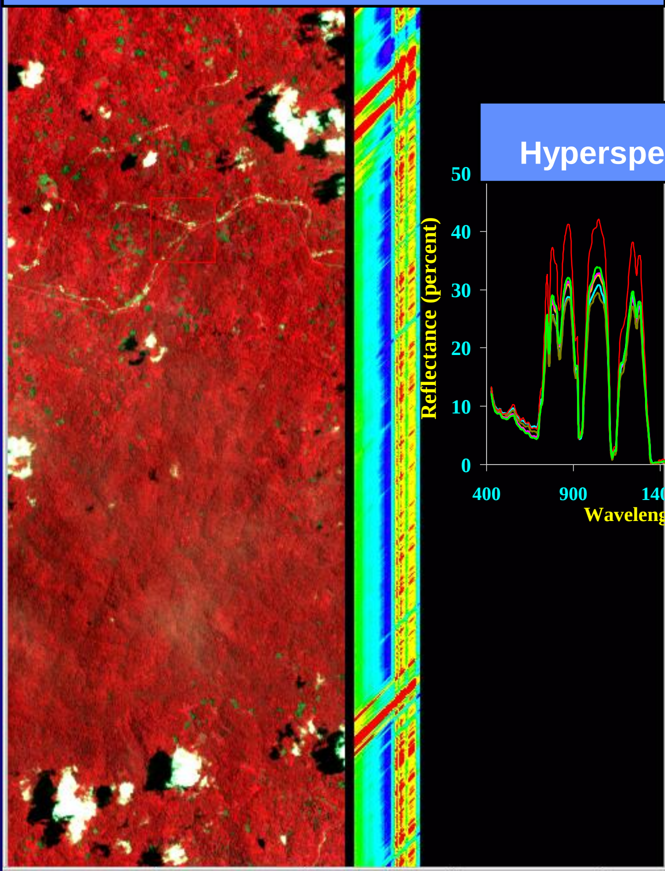


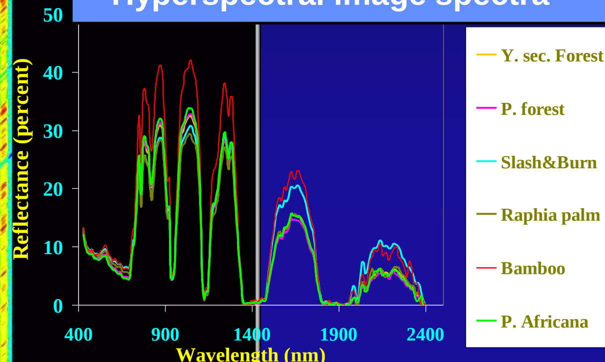
Hyperspectral Remote Sensing of Vegetation: Knowledge Gain and Knowledge Gap After 40 years of Research

Generating Broadbands (e.g., Landsat, IKONOS) from Narrowbands (e.g., HyspIRI)

Hyperspectral image data cube

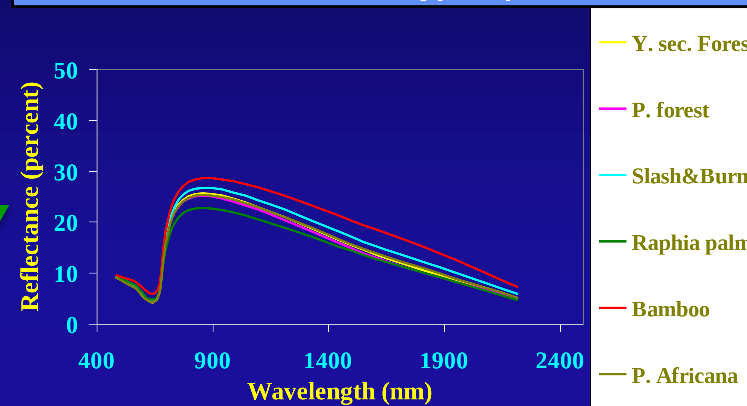


Hyperspectral image spectra

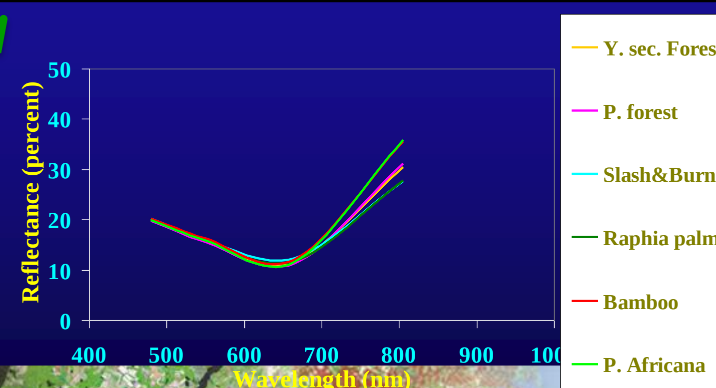


Imaging spectroscopy: 242 hyperspectral bands, each of 5 or 10 nm wide, in 400-2500 nm spectral range.

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



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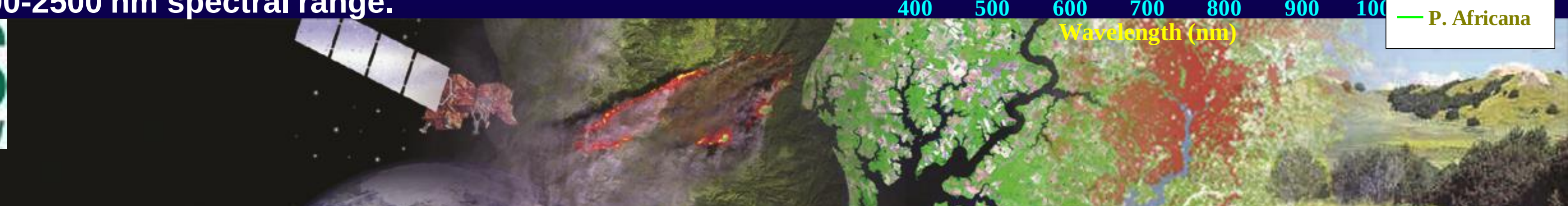

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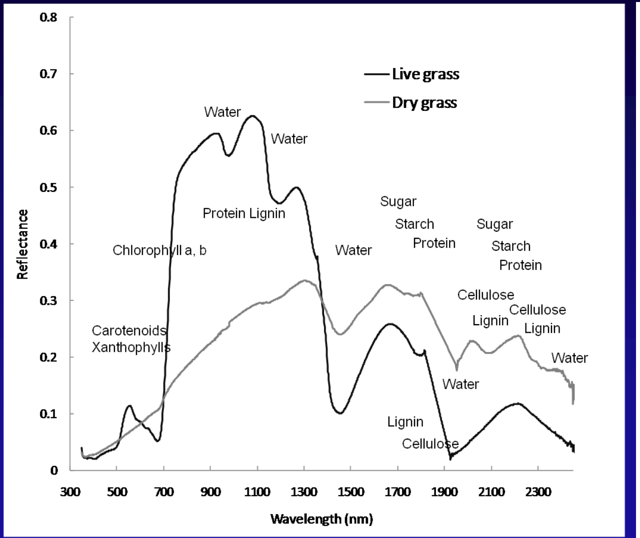
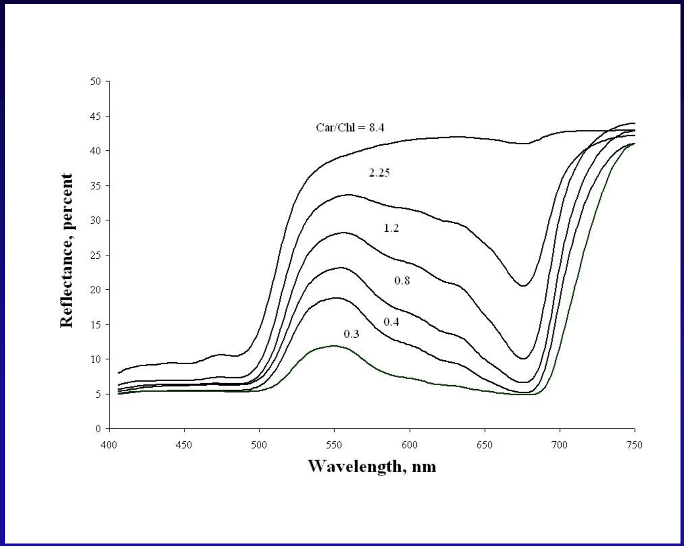
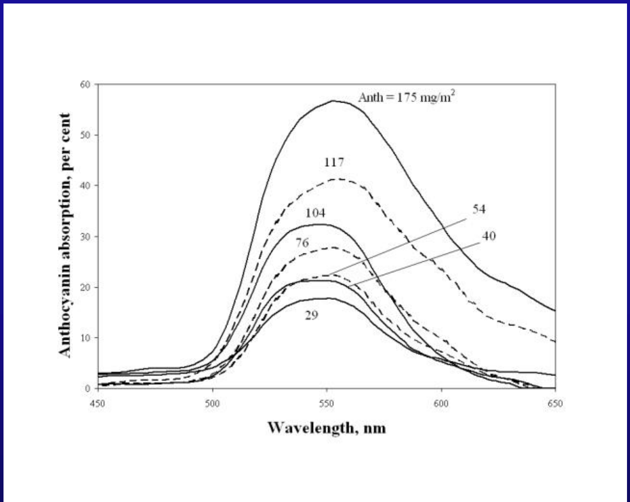
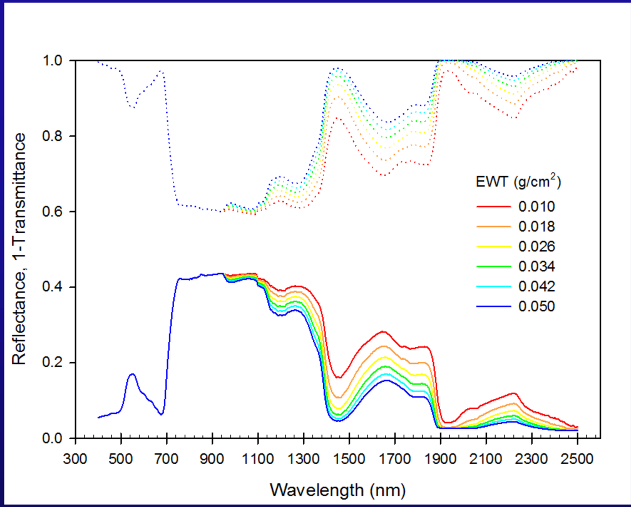
Hyperspectral Remote Sensing of Vegetation: Knowledge Gain and Knowledge Gap After 40 years of Research

Specific Targeted Portion of the Spectrum to Study Specific Biophysical and Biochemical Property









It is also important to know what specific wavebands are most suitable to study particular biophysical and/or biochemical properties. As examples, plant moisture sensitivity is best studied using a narrowband (5 nm wide or less) centered at 970 nm, while plant stress assessments are best made using a red-edge band centered at 720 nm (or an first order derivative index derived by integrating spectra over 700-740 nm range), and biophysical variables are best retrieved using a red band centered at 687 nm. These bands are, often, used along with a reference band to produce an effective index such as a two-band normalized difference vegetation index involving a near infrared (NIR) reference band centered at 890 nm and a red band centered at 687 nm.

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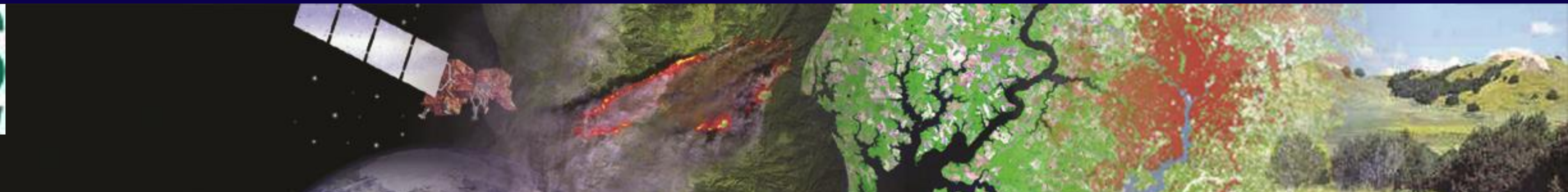

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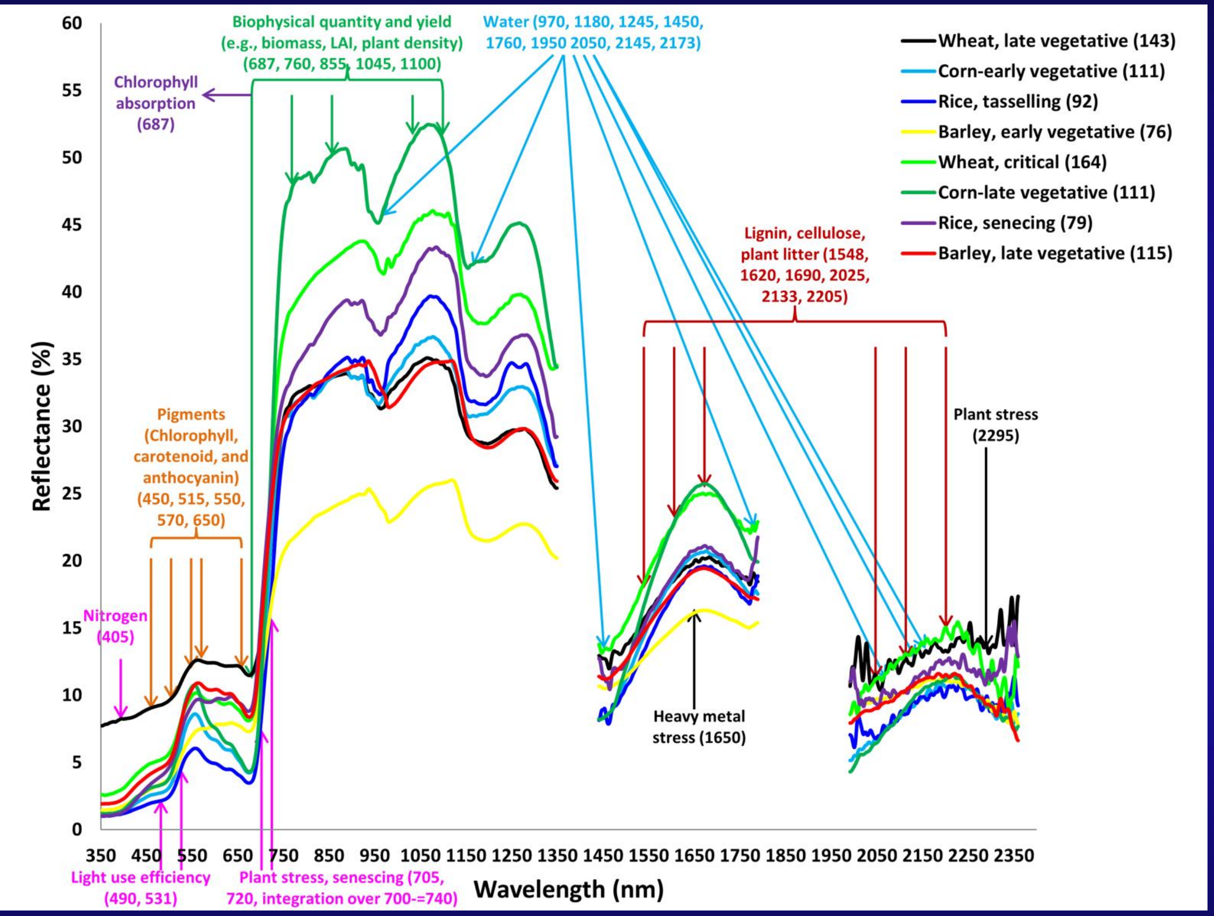
Hyperspectral (Imaging Spectroscopy) Narrowband Study of Agricultural Crops

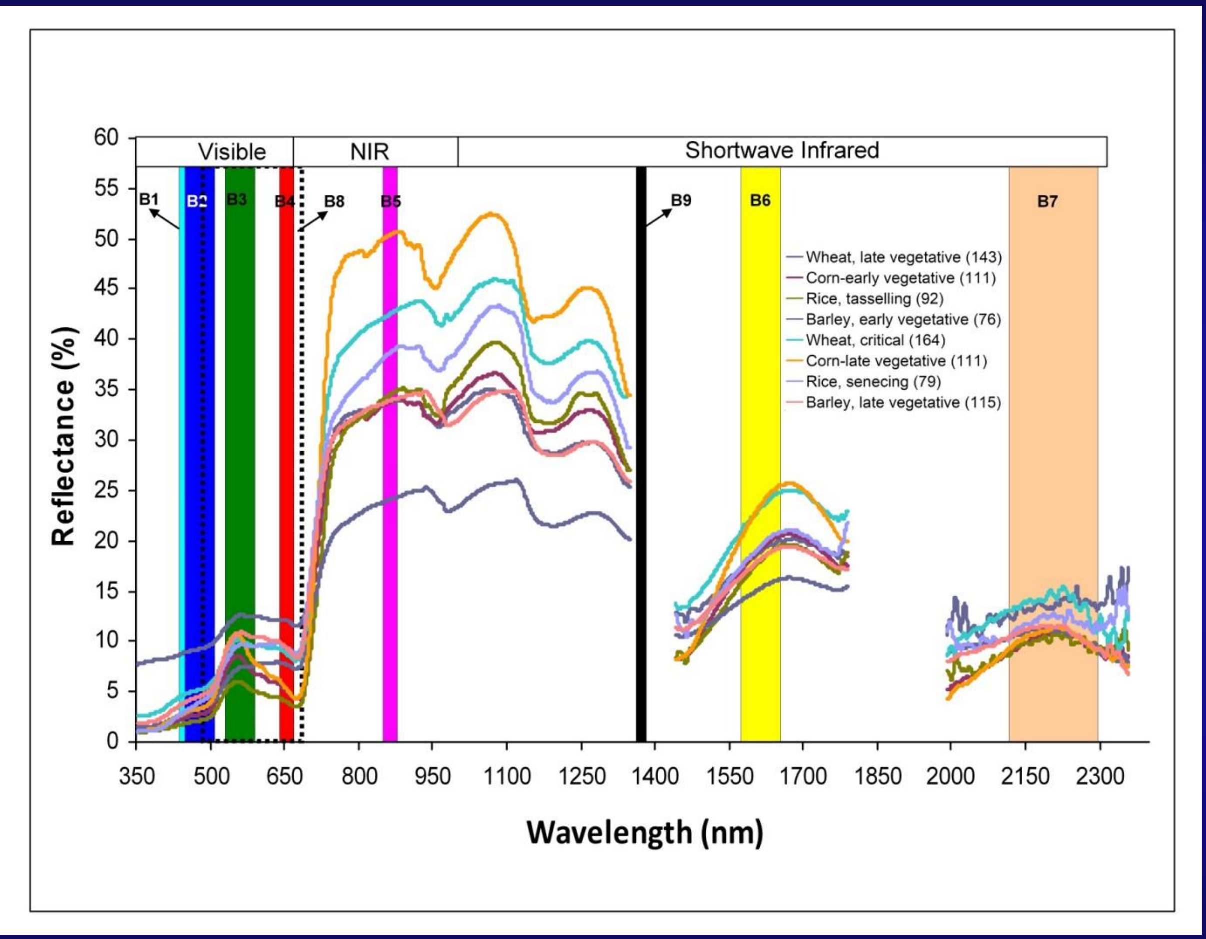
Optimal Hyperspectral Narrowbands in Study of Agriculture



Optimal hyperspectral narrowbands (HNBs). Current state of knowledge on hyperspectral narrowbands (HNBs) for agricultural and vegetation studies (inferred from [8]). The whole spectral analysis (WSA) using contiguous bands allow for accurate retrieval of plant biophysical and biochemical quantities using methods like continuum removal. In contrast, studies on wide array of biophysical and biochemical variables, species types, crop types have established: (a) optimal HNBs band centers and band widths for vegetation/crop characterization, (b) targeted HVIs for specific modeling, mapping, and classifying vegetation/crop types or species and parameters such as biomass, LAI, plant water, plant stress, nitrogen, lignin, and pigments, and (c) redundant bands, leading to overcoming the Hughes Phenomenon. These studies support hyperspectral data characterization and applications from missions such as Hyperspectral Infrared Imager (HyspIRI) and Advanced Responsive Tactically Effective Military Imaging Spectrometer (ARTEMIS). Note: sample sizes shown within brackets of the figure legend refer to data used in this study.

Hyperspectral (Imaging Spectroscopy) Narrowband Study of Agricultural Crops

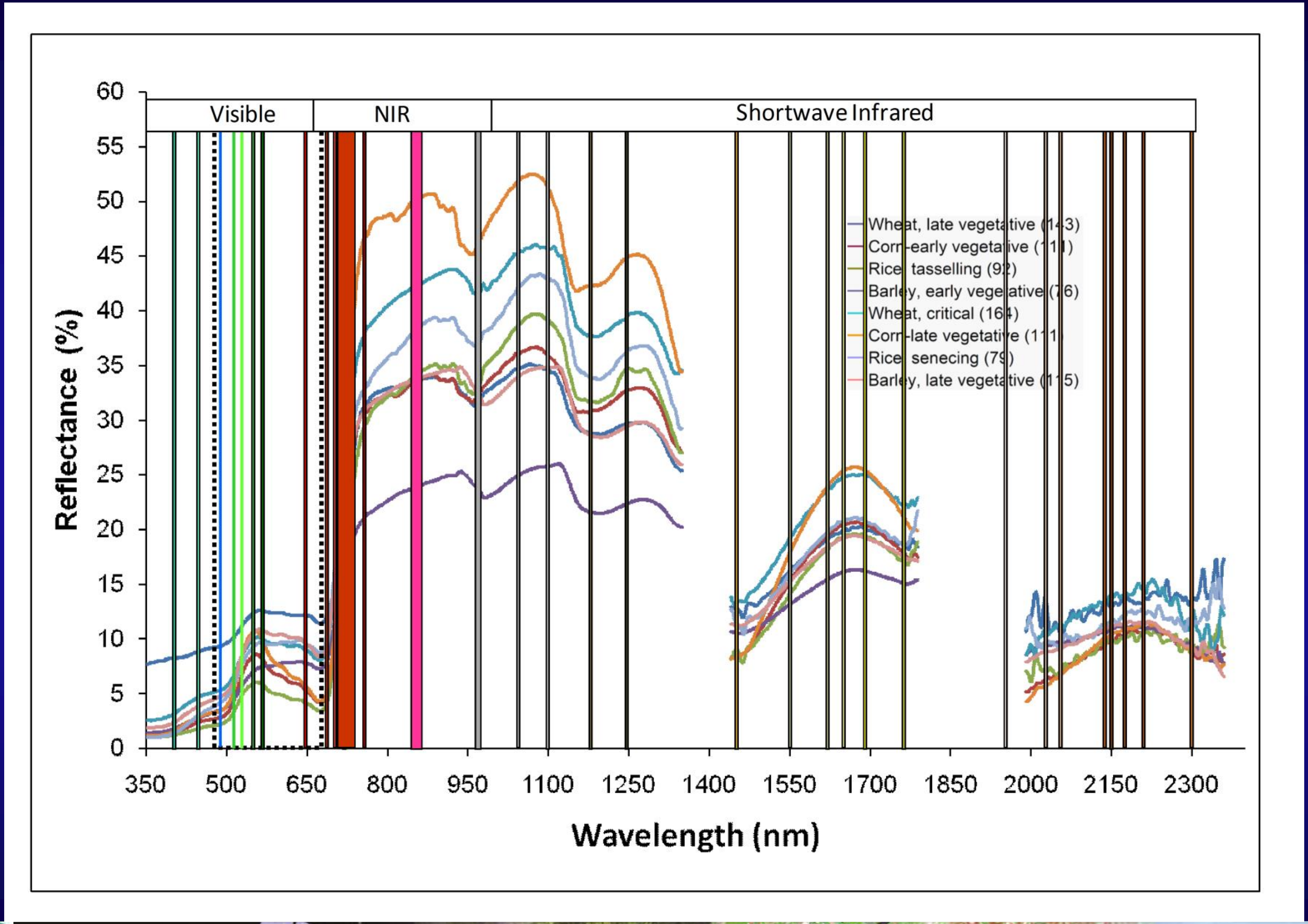
Hyperspectral Narrowbands versus Multispectral Broadbands

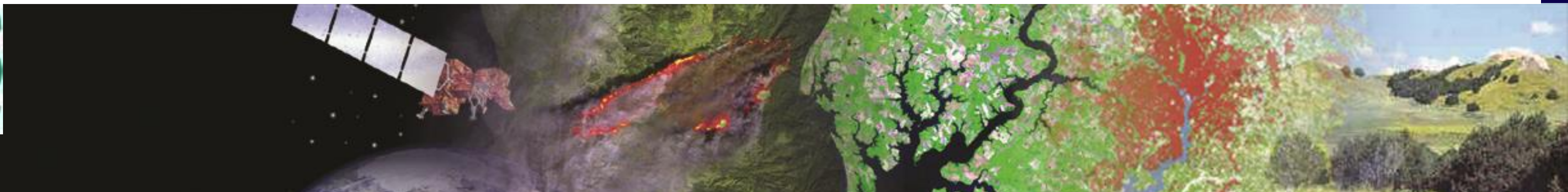


Optimal hyperspectral narrowbands (HNBs). Current state of knowledge on hyperspectral narrowbands (HNBs) for agricultural and vegetation studies (inferred from [8]). The whole spectral analysis (WSA) using contiguous bands allow for accurate retrieval of plant biophysical and biochemical quantities using methods like continuum removal. In contrast, studies on wide array of biophysical and biochemical variables, species types, crop types have established: (a) optimal HNBs band centers and band widths for vegetation/crop characterization, (b) targeted HVIs for specific modeling, mapping, and classifying vegetation/crop types or species and parameters such as biomass, LAI, plant water, plant stress, nitrogen, lignin, and pigments, and (c) redundant bands, leading to overcoming the Hughes Phenomenon. These studies support hyperspectral data characterization and applications from missions such as Hyperspectral Infrared Imager (HyspIRI) and Advanced Responsive Tactically Effective Military Imaging Spectrometer (ARTEMIS). Note: sample sizes shown within brackets of the figure legend refer to data used in this study.

Hyperspectral Narrowband Study of Agricultural Crops

33 Optimal Hyperspectral narrowbands (HNBs) in study of Agriculture and Vegetation





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Hyperspectral (Imaging Spectroscopy) Narrowband Study of Agricultural Crops
Best Hyperspectral Multiple Narrowband Combinations in Study of Agriculture

Table 3: The best 4, 6, 10, 15, and 20 band combinations of hyperspectral narrowbands (HNBs) for separating or discriminating crop types or classifying them.

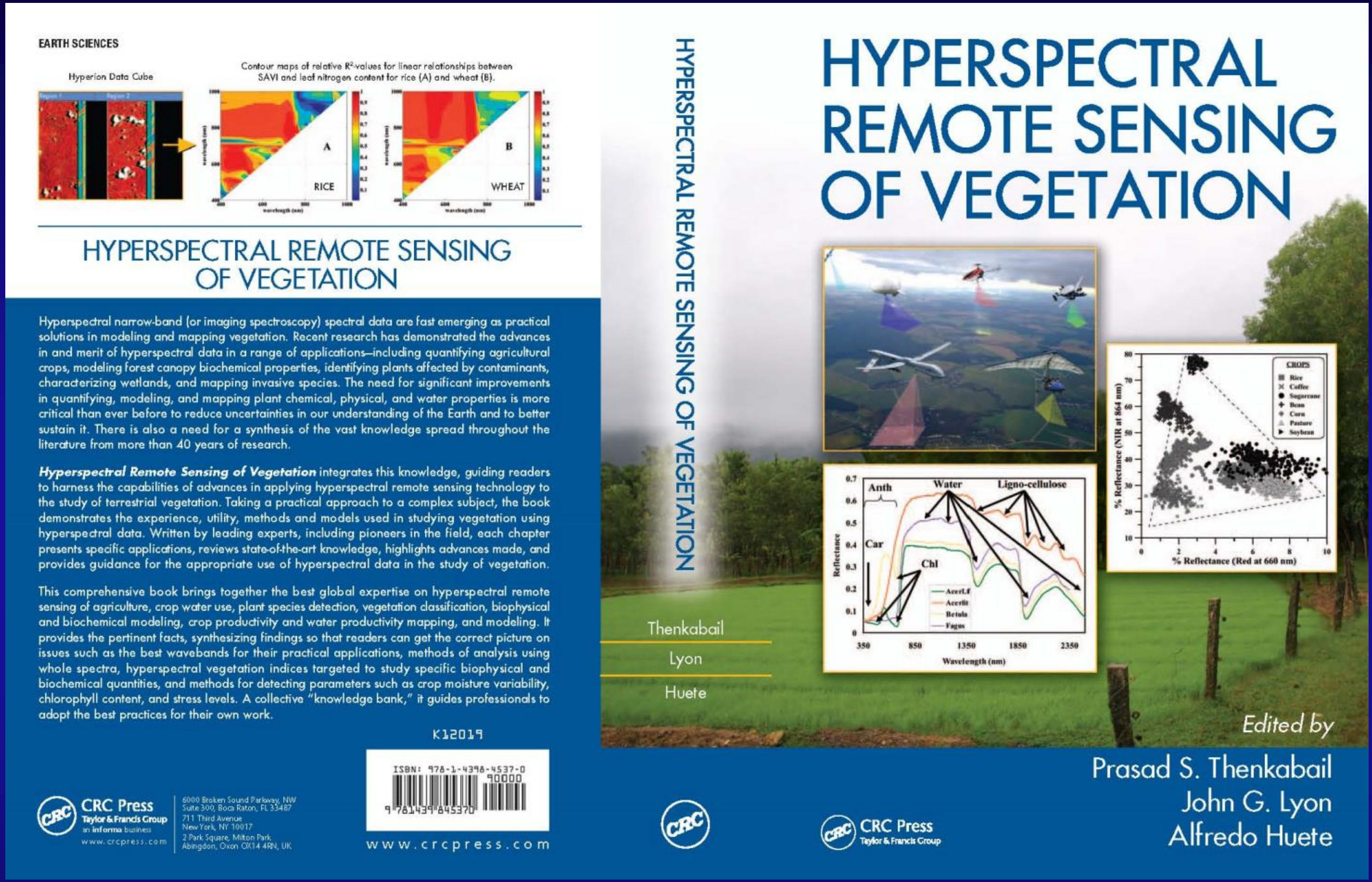
Best 4 bands	550, 687, 855, 1180 nm
Best 6 bands	550, 687, 855, 1180, 1650, 2205 nm
Best 10 bands	550, 687, 720, 855, 970, 1180, 1245, 1450, 1650, 2205 nm
Best 15 bands	515, 550, 650, 687, 720, 760, 855, 970, 1110, 1180, 1245, 1450, 1650, 1950, 2205 nm
Best 20 bands	490, 515, 531, 550, 570, 650, 687, 720, 760, 855, 970, 1045, 1110, 1180, 1245, 1450, 1650, 1760, 1950, 2205 nm

Publications

Hyperspectral Remote Sensing of Vegetation

Hyperspectral Remote Sensing (Imaging Spectroscopy) for Vegetation Studies

References Pertaining to this Presentation



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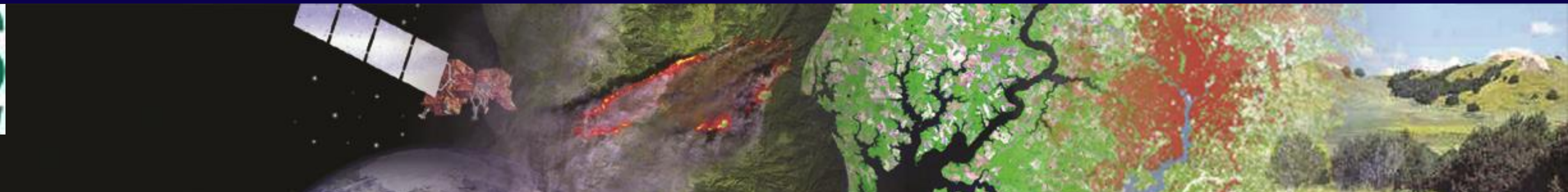

Hyperspectral Remote Sensing (Imaging Spectroscopy) for Vegetation Studies

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PE&RS Special Issue: Articles due Oct. 1, 2013

PE&RS Special Issue

Hyperspectral Remote Sensing of Vegetation and Agricultural Crops

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Hyperspectral remote sensing is fast emerging as a key technology for advanced and improved understanding, classification, modeling, monitoring, and mapping of complex terrestrial vegetation and agricultural crops. The advent of hyperspectral sensors or imaging spectroscopy (e.g., NASA's Hyperion, ESA's PROBA, and upcoming Italy's ASI's Prisma, Germany's DLR's EnMAP, Japanese HIUSI, NASA's HyspIRI) as well as the advancements in processing large volumes of data have further generated tremendous interest in expanding the hyperspectral applications' knowledge base over large areas including the entire globe as envisaged in Hyperspectral Infrared Imager (HyspIRI) mission and, potentially, even in the future Landsats (e.g., Landsat-9 may have a Hyperspectral sensor). Even though many advances have been made (see recent book on "*Hyperspectral Remote Sensing of Vegetation*" by edited Thenkabail, Lyon, and Huete; published by Taylor and Francis) knowledge-gap in our understanding, classification, modeling, monitoring, and mapping of vegetation and agricultural crops using hyperspectral narrowbands (HNBs) and\or hyperspectral vegetation indices (HVIs) continues to be quite high. For example, at present substantial uncertainties exist in the selection of optimized HNBs and HVIs as a result of the lack of integrated global studies that take into consideration: (a) wide array of forest species in range of environments; (b) agricultural crops grown in distinct agroecosystems, (c) large number of crops that occupy overwhelming proportion of cropland areas, and (d) robust models developed based on diverse representative areas, wide array of crops, and numerous biophysical and biochemical characteristics. Further, we expect substantial new and enhanced knowledge by using hyperspectral thermal infrared bands (HTIRBs) in addition to HNBs and HVIs.

The goal of this special issue is to seek papers on wide array of topics that contribute to advancement of knowledge in use of hyperspectral remote sensing studies of terrestrial vegetation and agricultural crops.

Papers on following topics are of particular interest:

1. **Overcoming Hughes phenomenon** (or the curse of high dimensionality) and identifying data redundancy of hyperspectral data by detecting and eliminating redundant bands through unique data mining techniques;
2. **Development and establishment of optimized hyperspectral-narrowband (HNBs), and Vegetation indices (HVIs)** for specific biophysical and biochemical characterization;
3. **Classification of complex vegetation and crop types\species using HNBs and HVIs** and compare them with the performance of multispectral broadband data;
4. **Whole spectral analysis** (e.g., continuous spectra over 400-13,000 nm) for advancement in our understanding and modeling of vegetation\crop structure, phenology, and quantity;
5. **Strengths and limitations** in use of: **A. Optimal number of narrowbands** (e.g., removing redundant bands) *versus* B. **Whole spectral analysis** (e.g., using continuum removal); to best characterize, classify, quantify, discriminate, and model vegetation\crop biophysical and biochemical quantities of vegetation\crops;
6. **Spectral libraries** of vegetation\crops and their role in advancement in our understanding of vegetation\crop characterization;
7. **Other methodological advances** in hyperspectral data analysis and modeling for vegetation and agricultural crops. Other innovative topics are equally welcome. Papers are welcome to use hyperspectral data from any platform (e.g., spaceborne, airborne, ground based). Papers of high societal benefit (e.g., food security, crop and water productivity, biomass\carbon modeling) and scientific missions (e.g., contributing to HyspIRI mission) are of particular interest. Studies can be local, regional, or global. All studies must address accuracies\errors\uncertainties.

All submissions will be peer-reviewed in line with PE&RS policy. Because of page limits, not all submissions recommended for acceptance by the review panel may be included in the special issue. Under this circumstance, the guest editors will select the most relevant papers for inclusion in the special issue. Authors must prepare manuscripts according to the PE&RS Instructions to Authors, published in each issue of PE&RS and also available on the ASPRS web site at http://www.asprs.org/pers/AuthorInstructions.

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