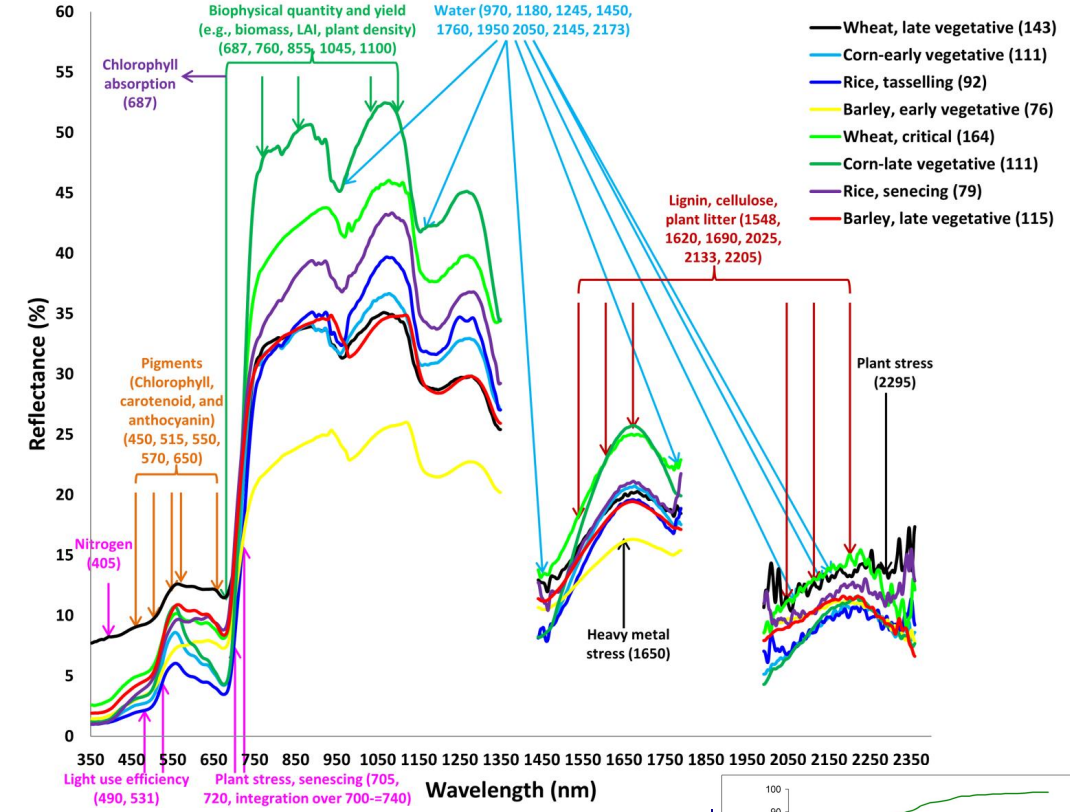
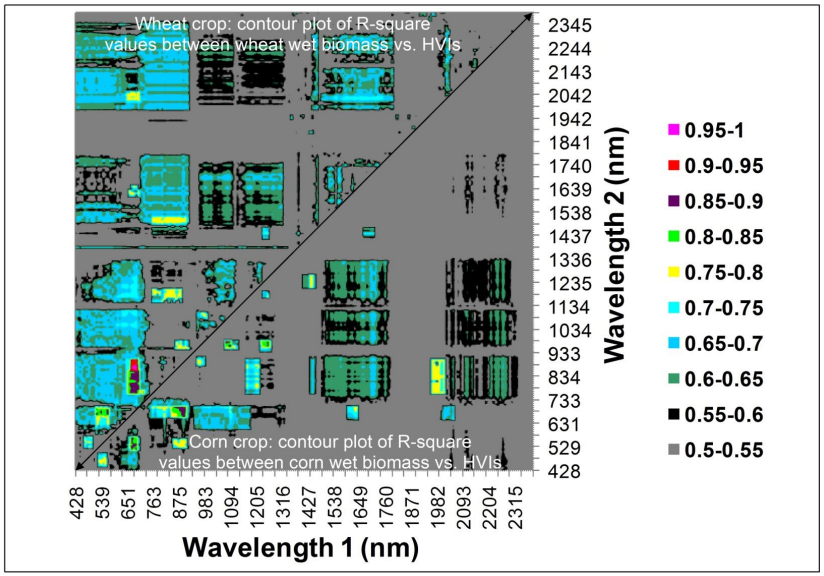
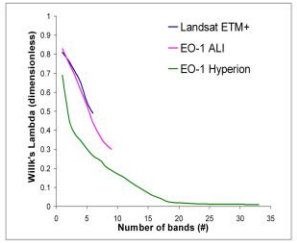
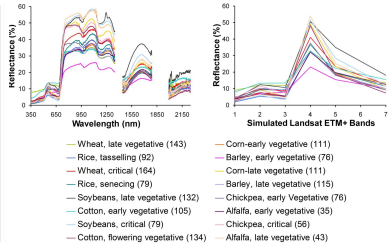
Hyperspectral remote sensing (imaging Spectroscopy) of agriculture and vegetation:

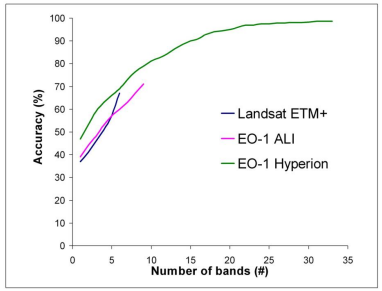
knowledge gains after 50 years of research

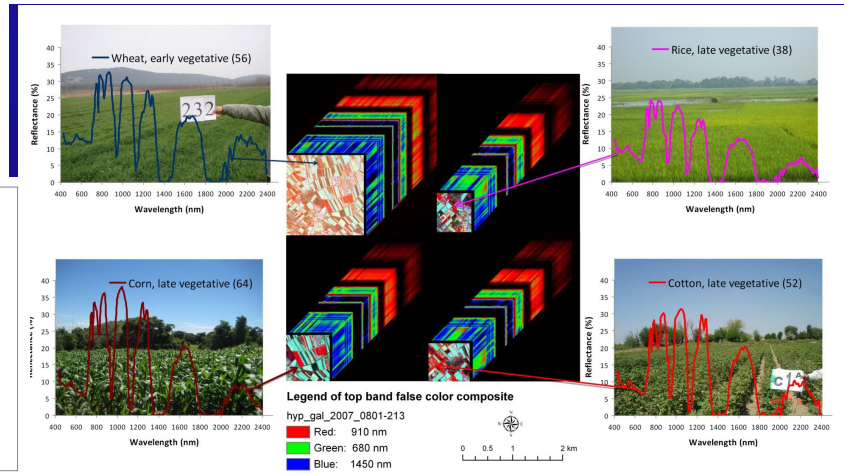












USGS science for a changing world

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

Dr. Prasad S. Thenkabail, PhD

Research Geographer-15, U.S. Geological Survey (USGS)

ISPRS SPEC3D workshop "Frontiers in Spectral imaging and 3D Technologies for Geospatial Solutions"

Jyväskylä, Finland, 25-27 October 2017

Hyperspectral Data Importance

in Study of Agriculture and Vegetation

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

Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation

Importance of Hyperspectral Sensors in Study of Vegetation

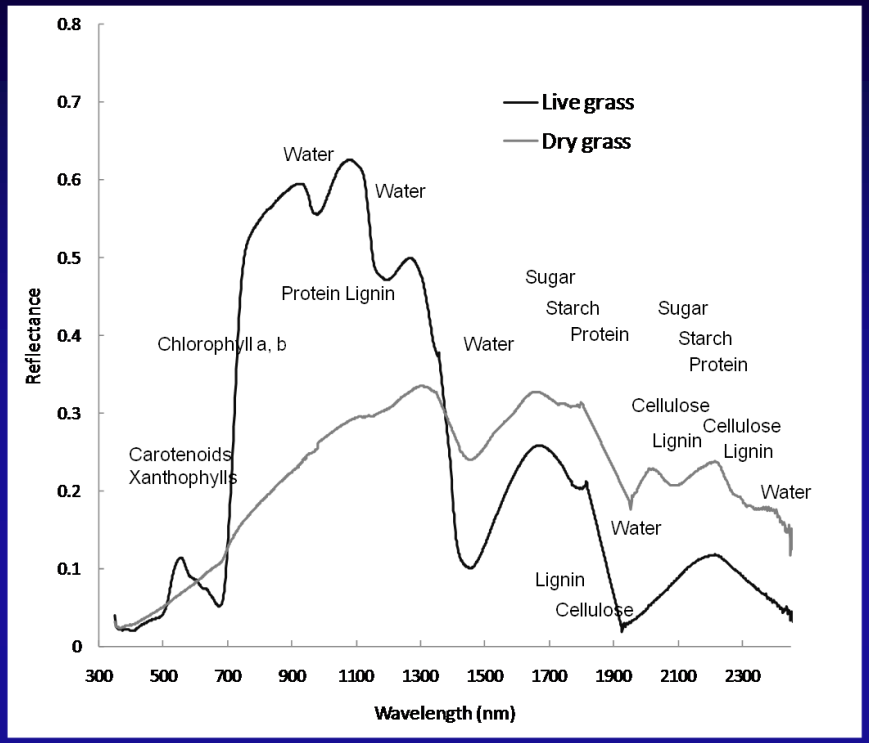
More specifically……..hyperspectral Remote Sensing, originally used for detecting and mapping minerals, is increasingly needed for to characterize, model, classify, and map agricultural crops and natural vegetation, specifically in study of:

(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.

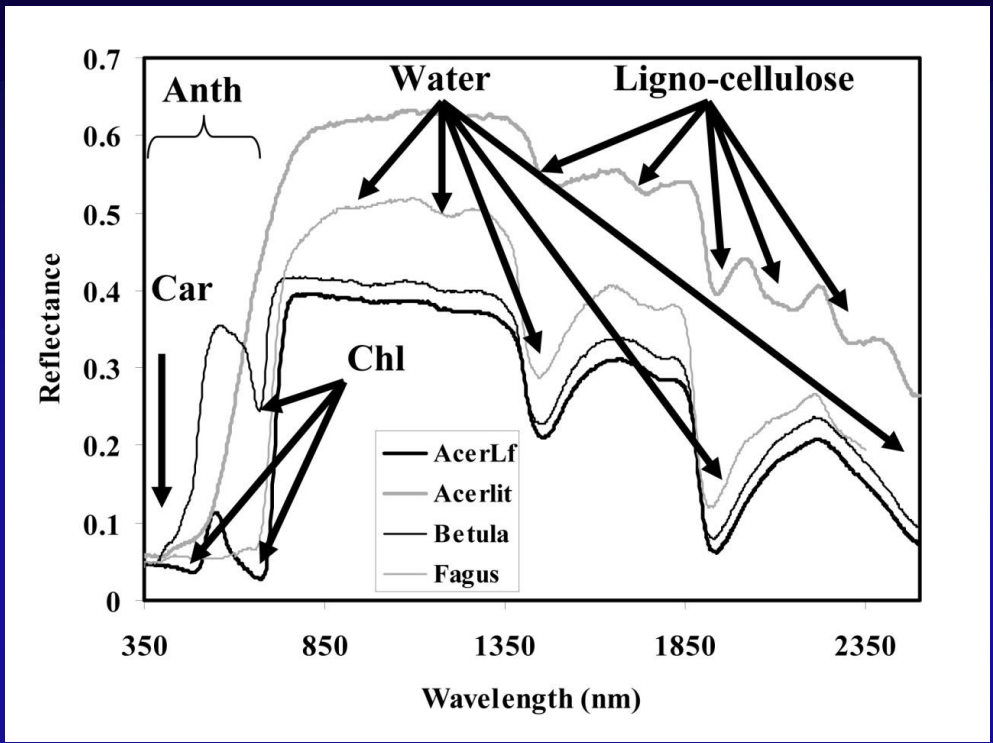
…….in order to increase accuracies and reduce uncertainties in these parameters……..

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 Definition

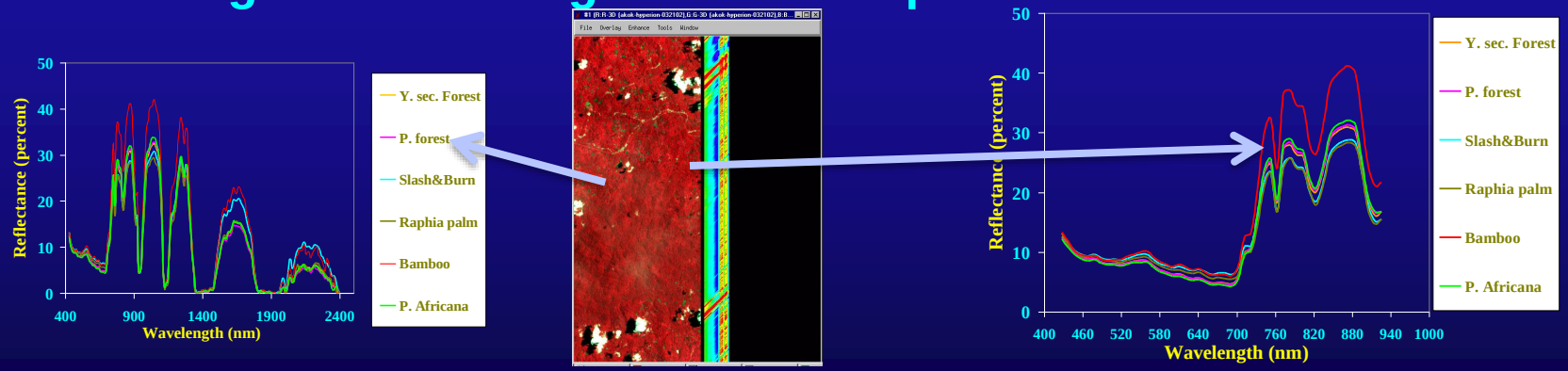
Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation

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 Sensors and their Characteristics

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

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

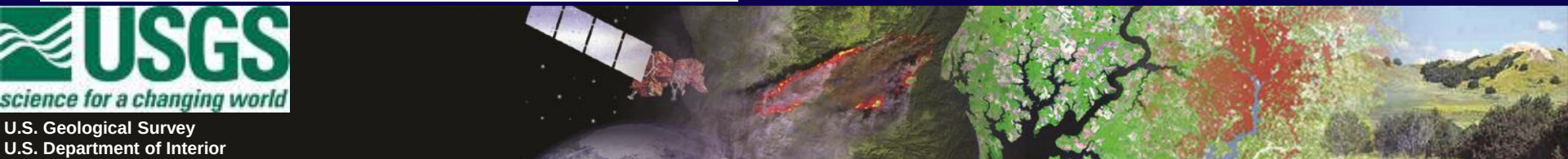
The advantages of spaceborne systems are their capability to acquire data: (a) continuously, (b) consistently, and (c) over the entire globe. A number of system design challenges of hyperspectral data are discussed in Chapter 3 by Qi et al. Challenges include cloud cover and large data volumes.

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 Sensors
Relative
to Multispectral Sensors

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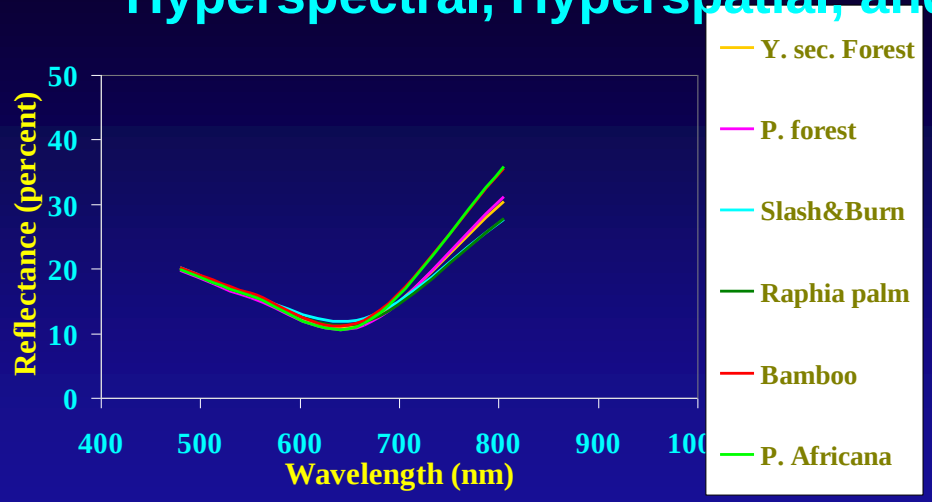
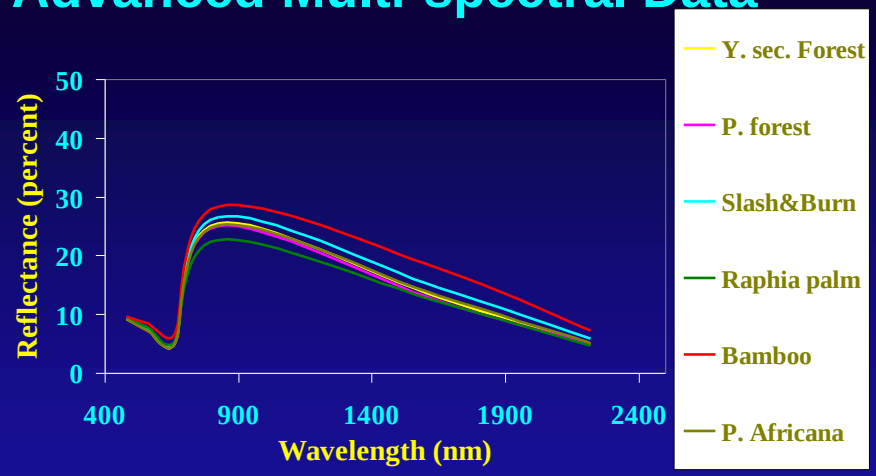
Comparison of Hyperspectral Data with Data from Other Advanced Sensors

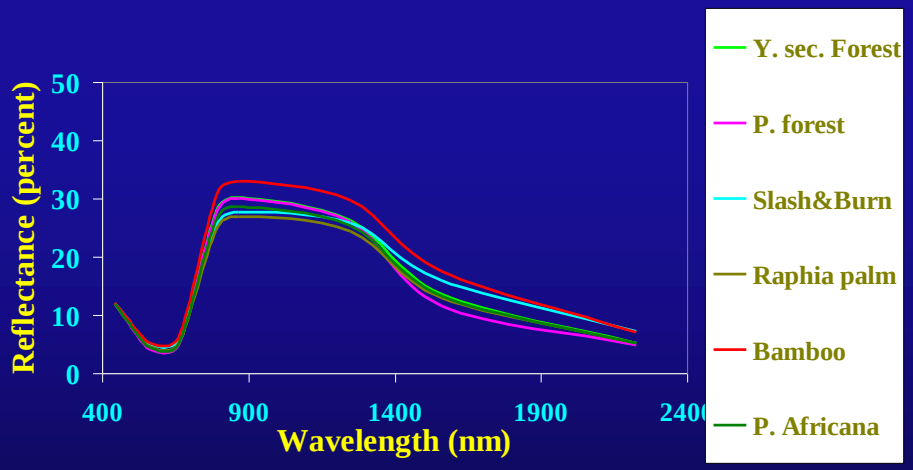
Hyperspectral, Hyperspatial, and Advanced Multi-spectral Data



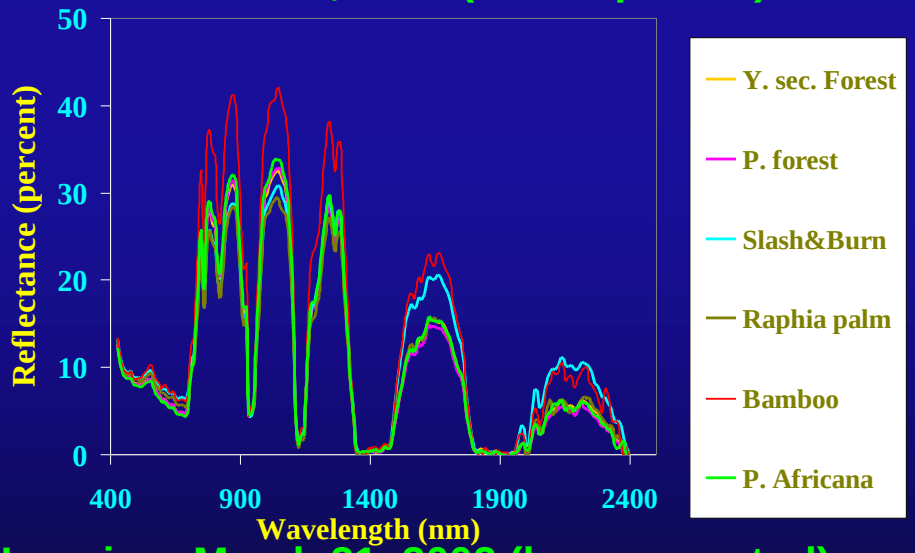
IKONOS: Feb. 5, 2002 (hyper-spatial)



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



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



Hyperion: March 21, 2002 (hyper-spectral)

Hyperion

the First Spaceborne Hyperspectral Sensor

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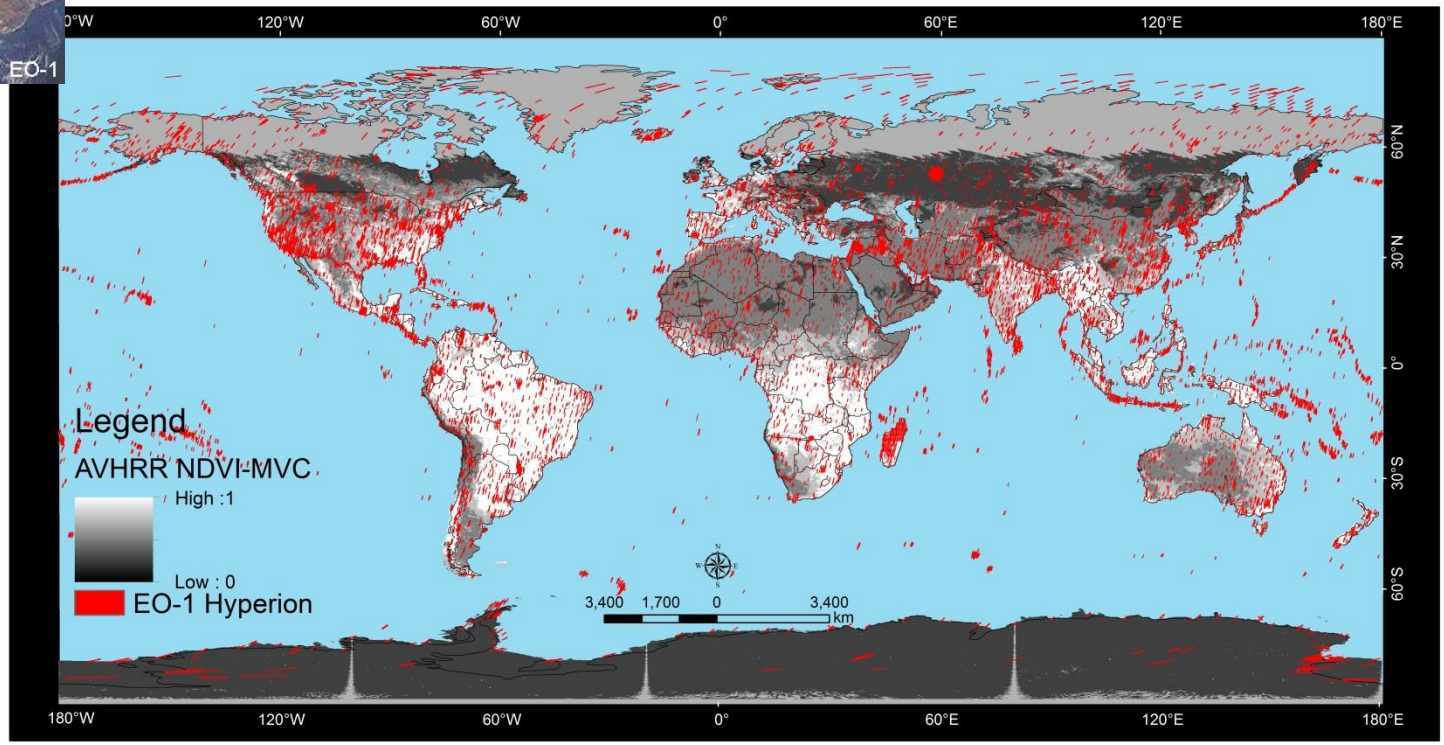
U.S. Department of Interior

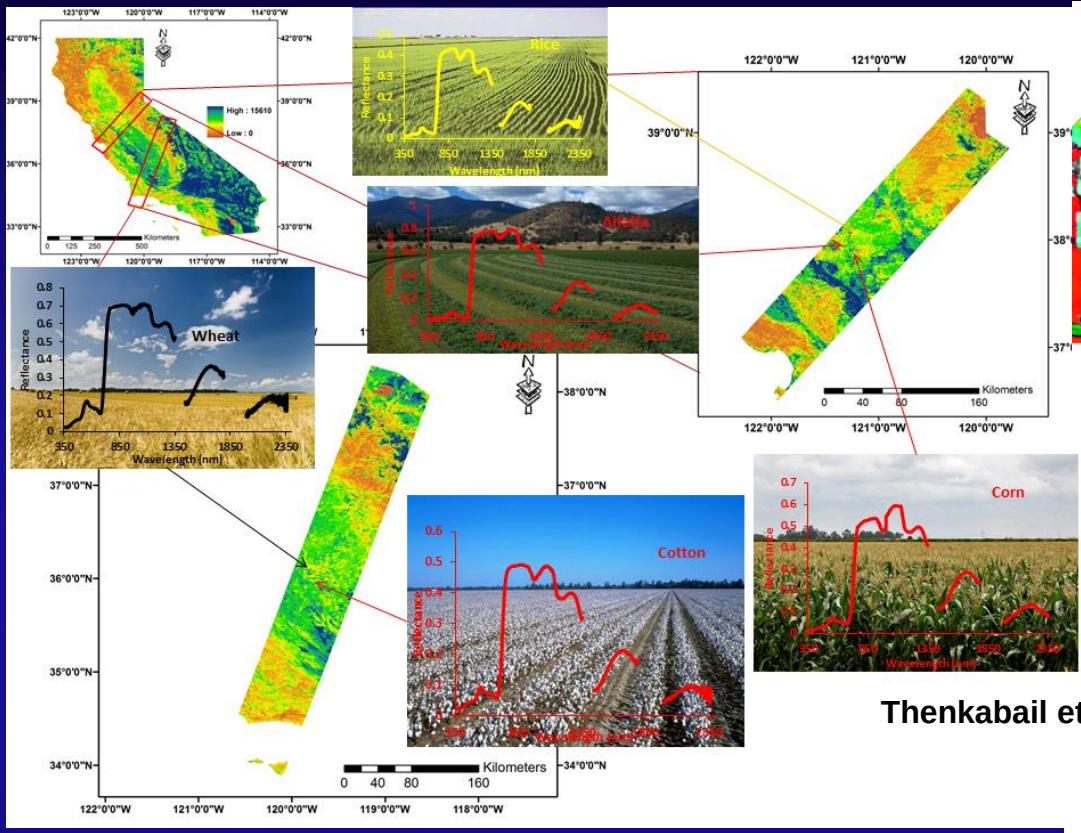
Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation
~70,000 Hyperspectral Hyperion Images of the World (2001-2013)

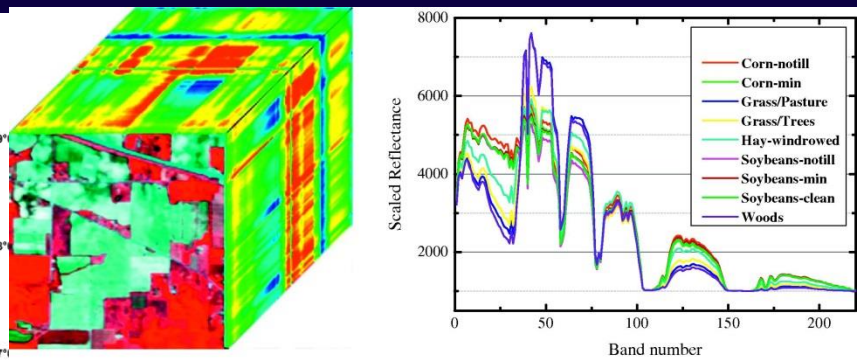
185 km by 7.5 km; 242 bands, 10 nm wide in 400-2500 nm; 30 m spatial resolution



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

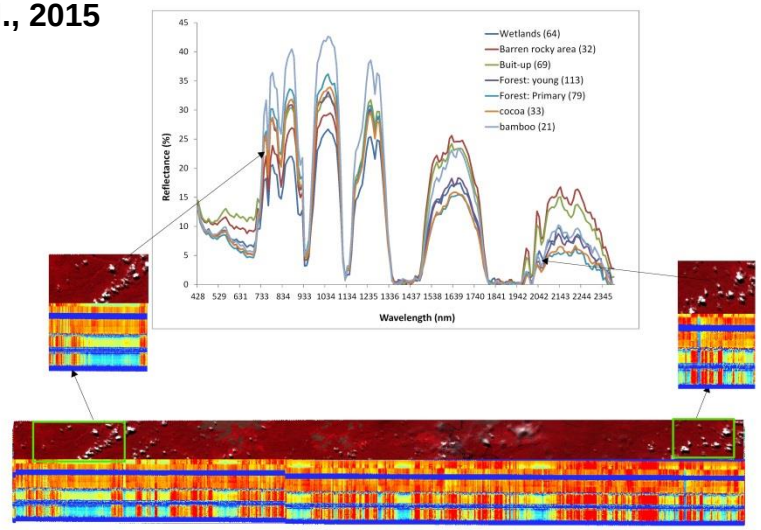
Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation
~70,000 Hyperspectral Hyperion Images of the World (2001-2013)





(a) Guo, X. et al., 2013 (b)

Thenkabail et al., 2015



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Hyperspectral Data
Characteristics in Study of Agriculture and Vegetation

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

Study of Biophysical Characteristics

1. Biomass: wet and dry; (kg\m^2);
2. Leaf area index (LAI), Green LAI; (m^2\m^2)
3. Plant height; (mm)
4. Vegetation fraction; (%)
5. Fraction of PAR absorbed by photosynthetically active vegetation (fAPAR); (MJ\m^2)
6. Total crop chlorophyll content; (g\m^2) and
7. Gross primary production. (g C\m^2\yr)

Note: see chapter 1, Thenkabail et al.; chapter 6, Gitelson et al.

Hyperspectral Data in Study of Complex Vegetation

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

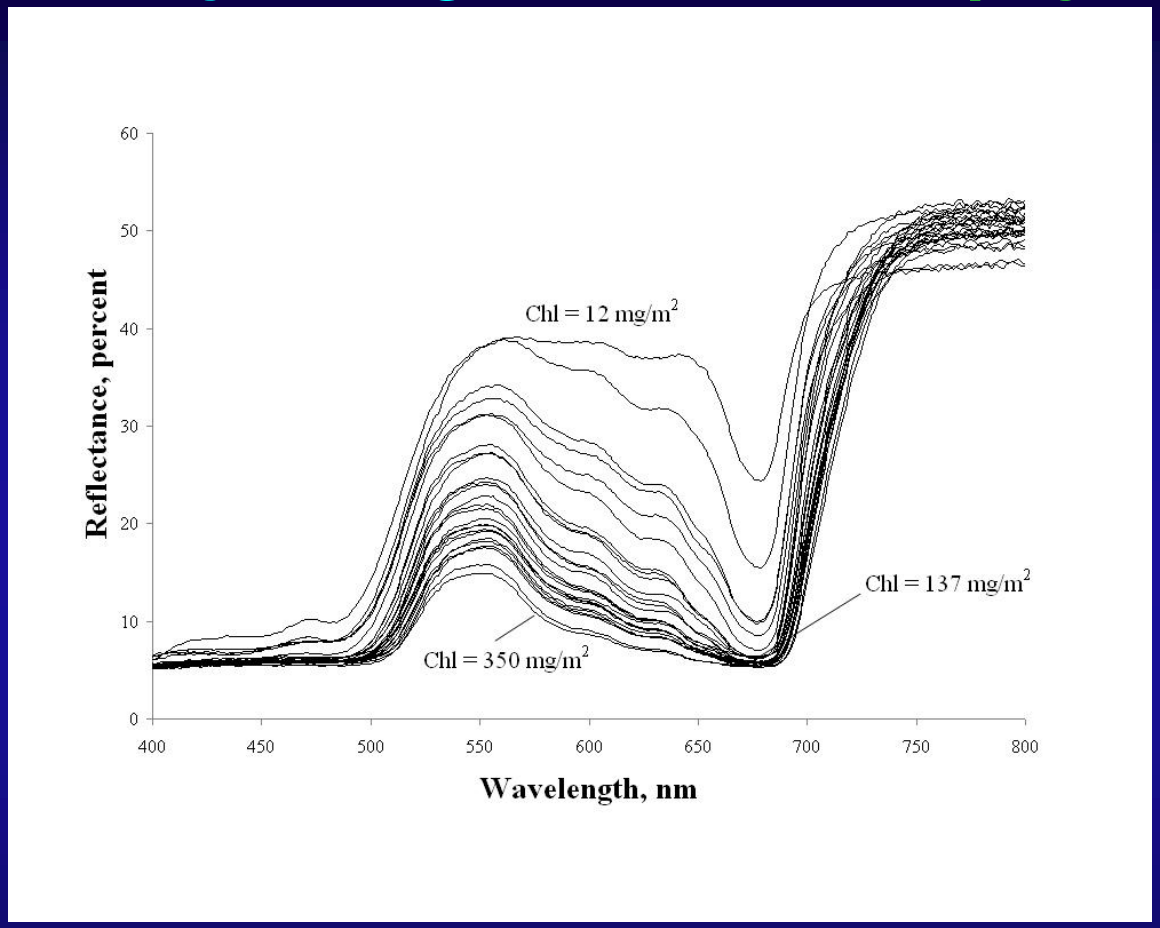
Biochemistry (e.g., plant pigments, water, and structural carbohydrates):
Leaf reflectance in the visible spectrum is dominated by absorption features created by plant pigments, such as:

- **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.

Hyperspectral Remote Sensing of Vegetation

Study of Pigments: chlorophyll

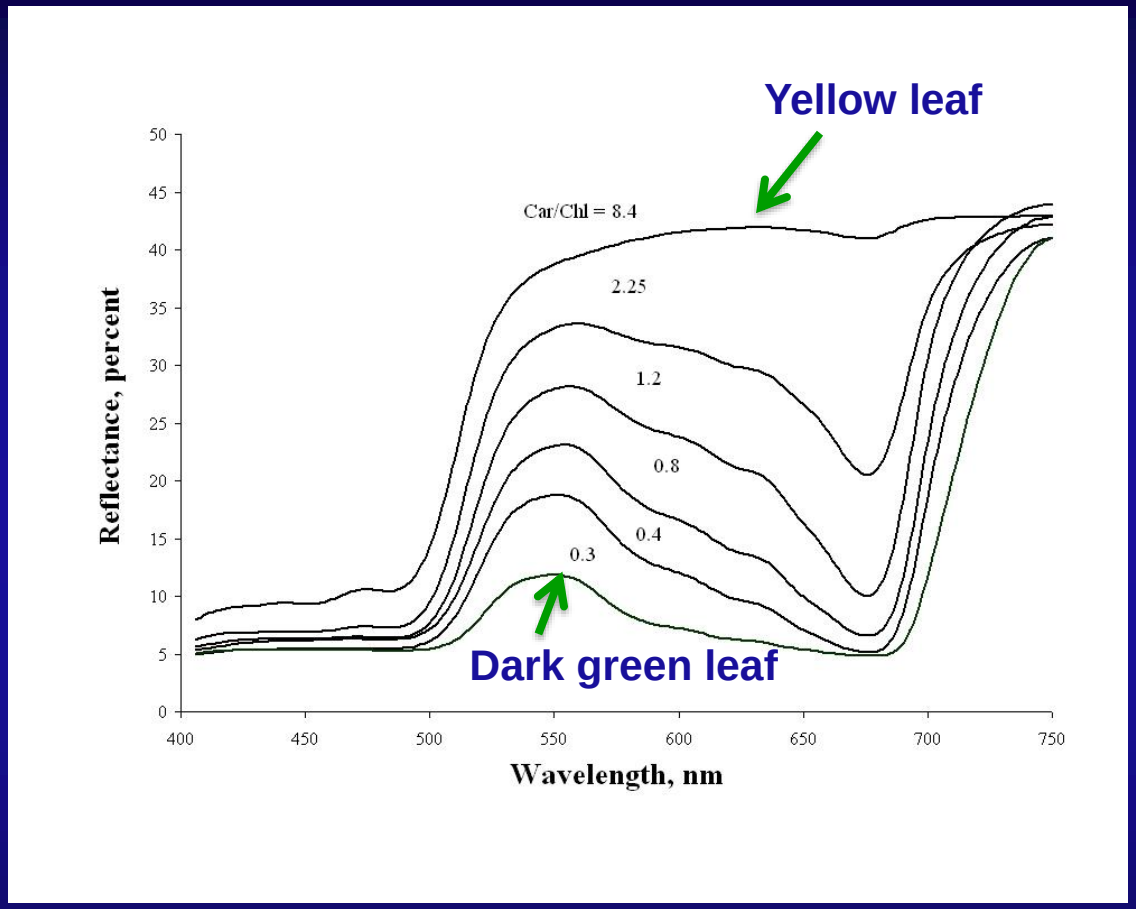


e.g., Reflectance spectra of beech leaves…red-edge (700-740 nm) one of the best.

Note: see chapter 6; Gitelson et al. (Book on "Hyperspectral Remote Sensing of Vegetation" (Editors: Thenkabail, Lyon, Huete)

Hyperspectral Remote Sensing of Vegetation

Study of Pigments: carotenoids/chlorophyll

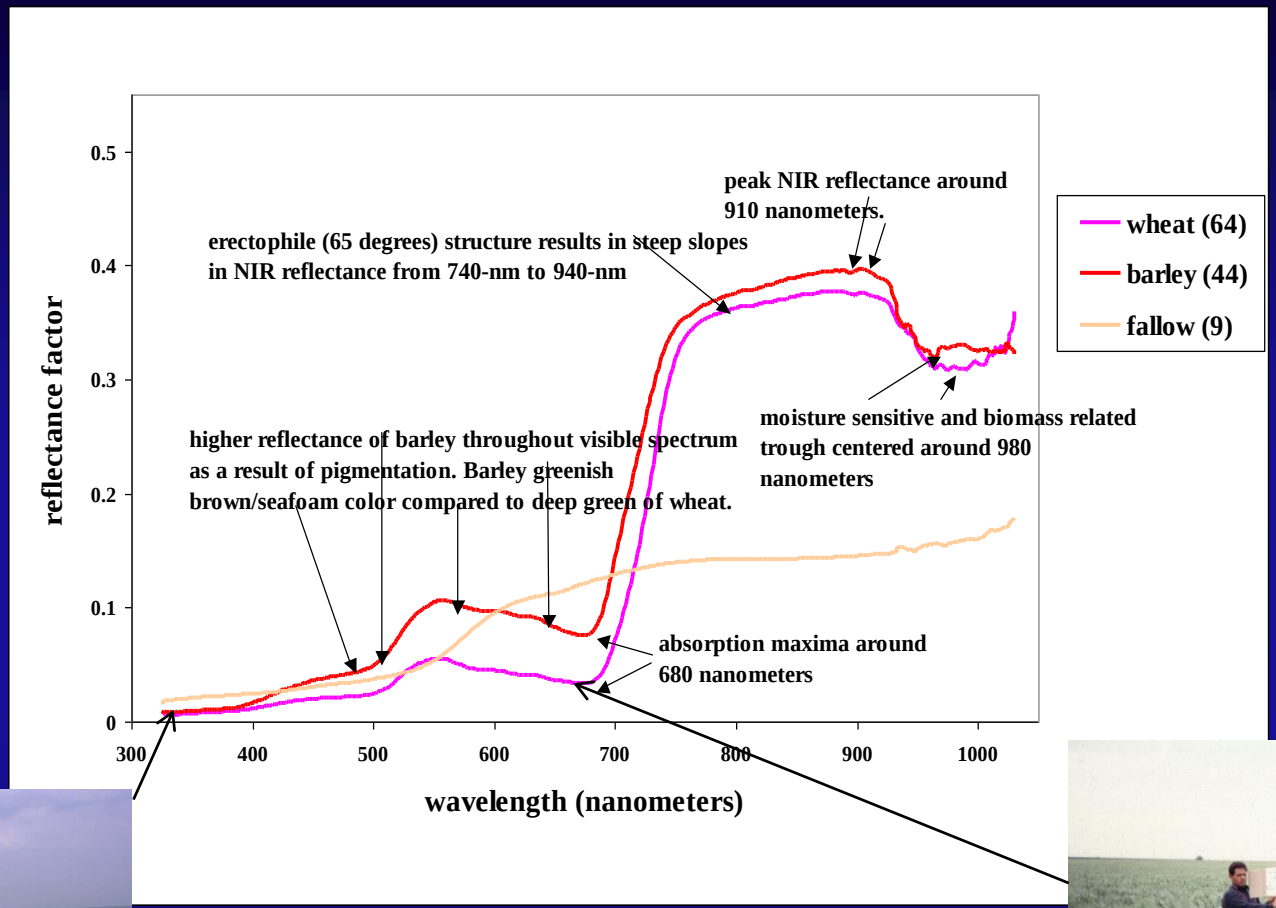


e.g., Reflectance spectra of chestnut leaves…difference reflectance of (680-500 nm)/750 nm quantitative measurement of plant senescence

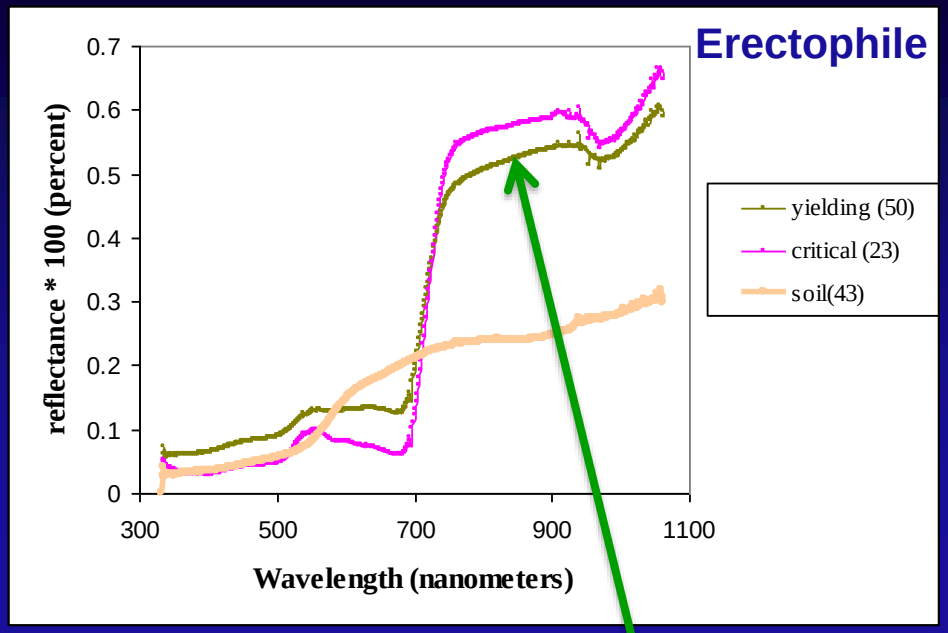
Note: see chapter 6; Gitelson et al. (Book on "Hyperspectral Remote Sensing of Vegetation" (Editors: Thenkabail, Lyon, Huete)

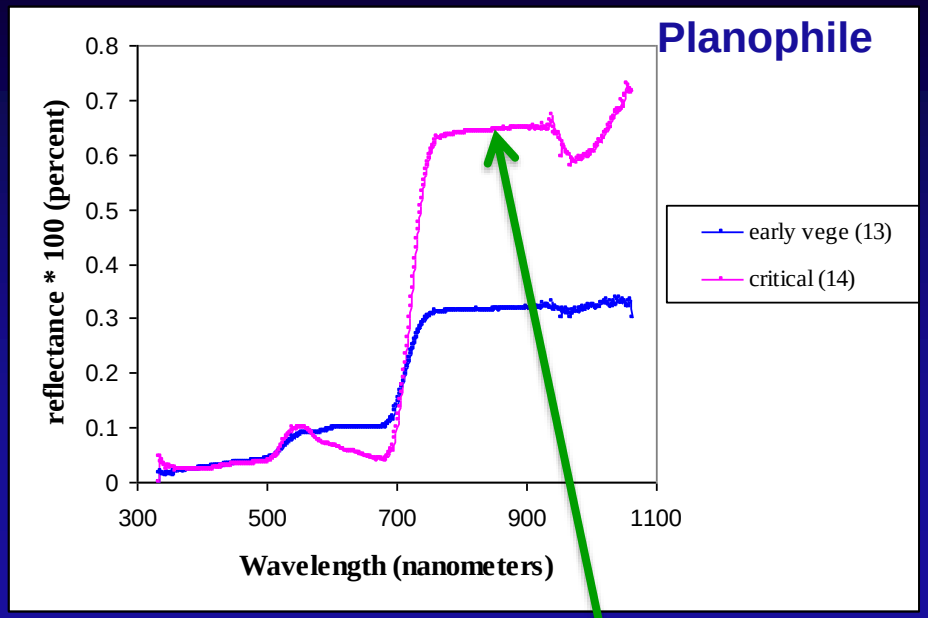
Wheat Crop Versus Barley Crop Versus Fallow Farm

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



Whole Spectral Analysis Versus Selective Optimal Bands

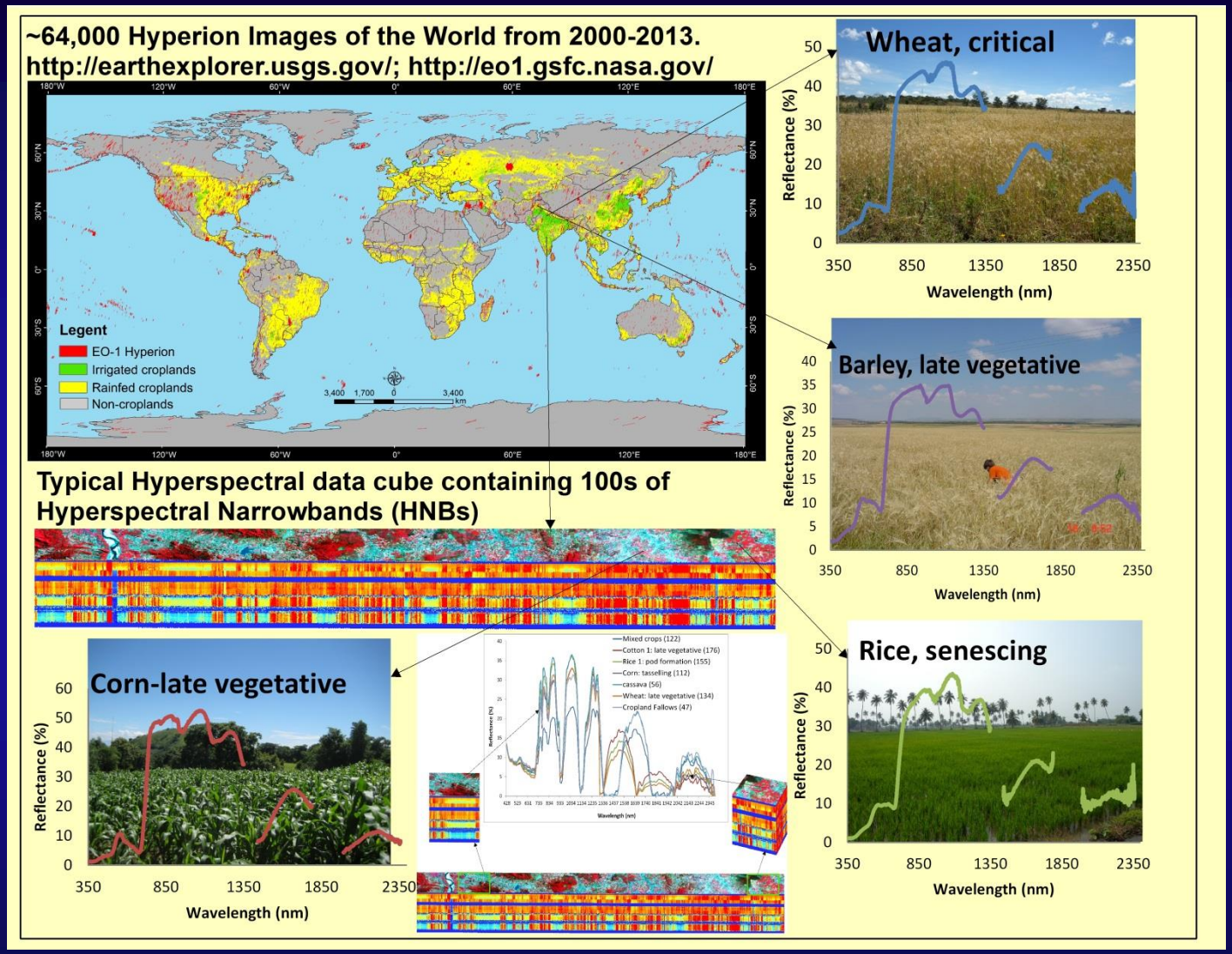




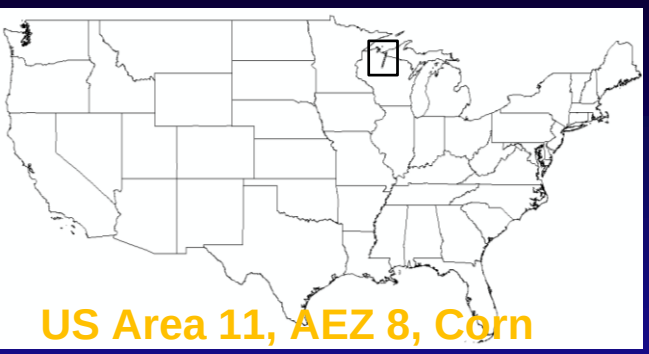
Rainforest Vegetation Studies: biomass, tree height, land cover, species

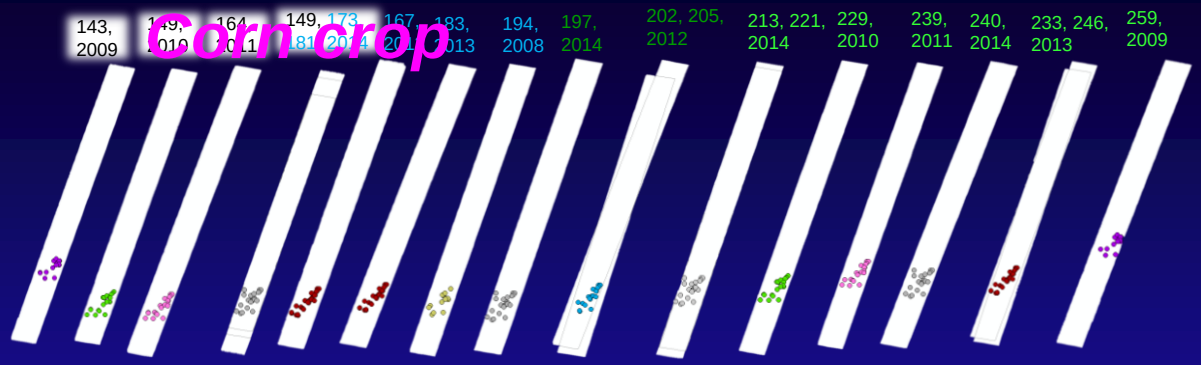
in African Rainforests

Hyperspectral Remote Sensing (Imaging Spectroscopy) of Vegetation
~70,000 Hyperspectral Hyperion Images of the World (2001-2015)

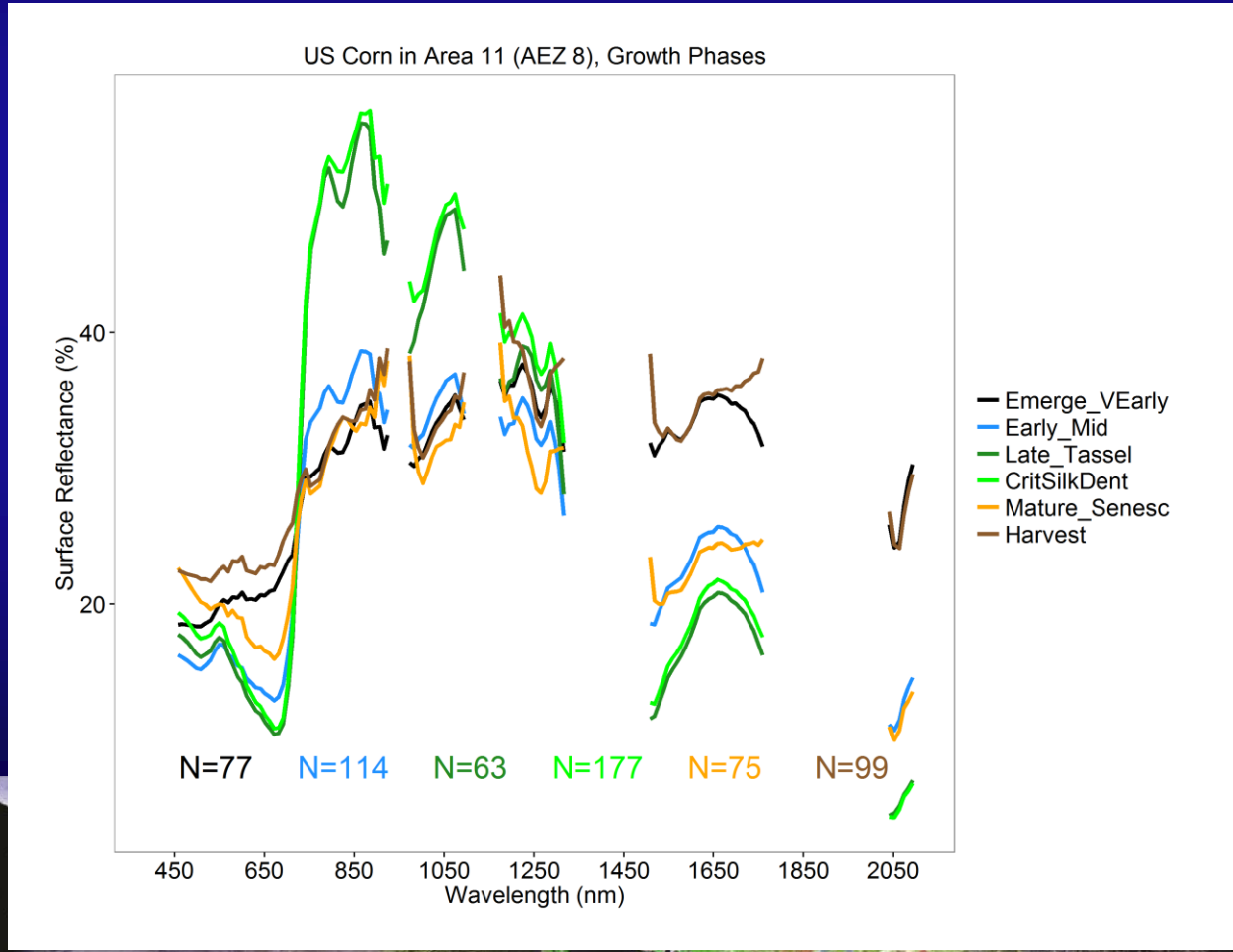


Hyperspectral Data of Agricultural Crops from EO-1 Hyperion: USA





*Colors for images are associated with years, not growth phases



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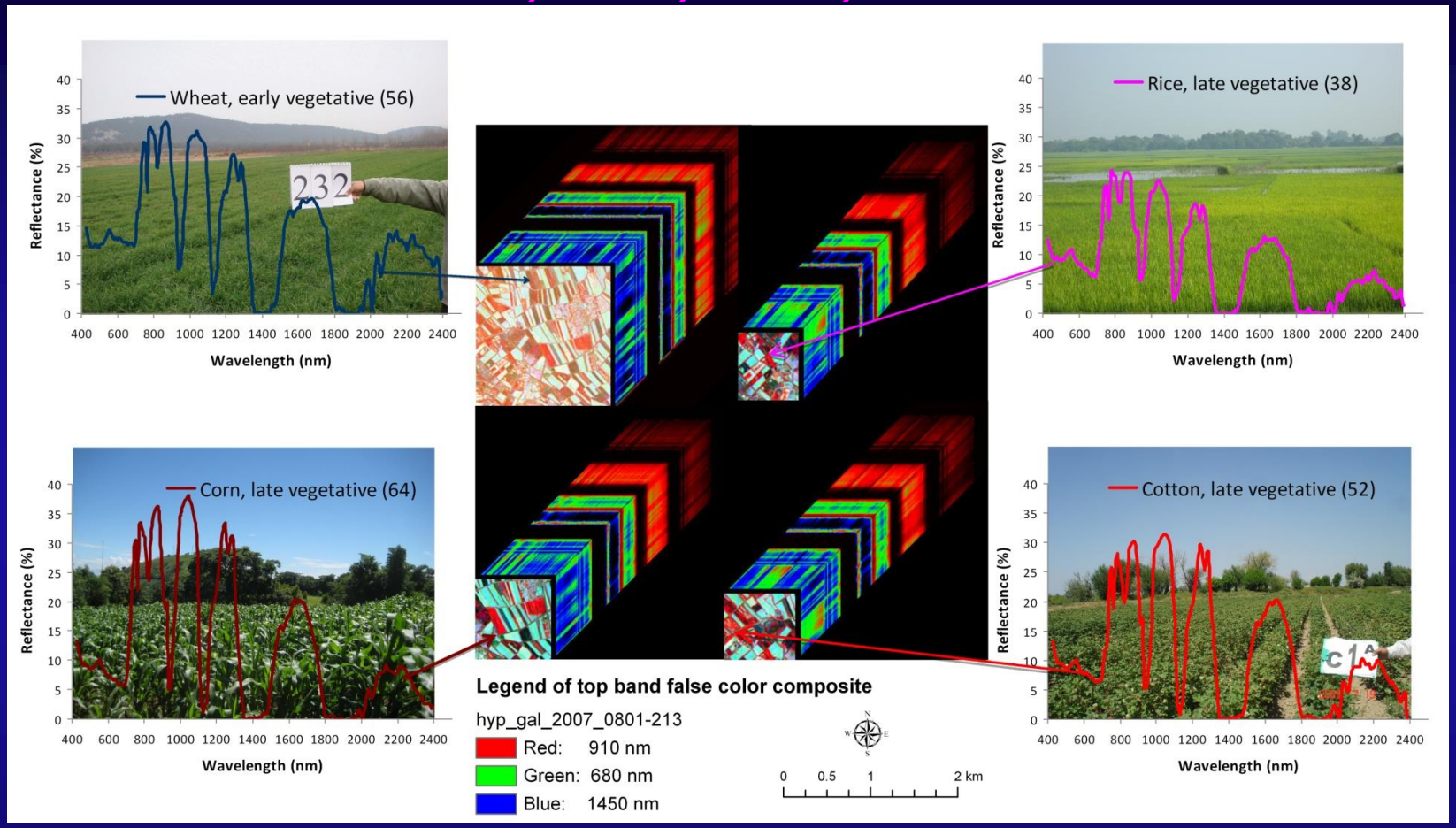
Hyperspectral Data of Agricultural Crops from EO-1 Hyperion: Central Asia

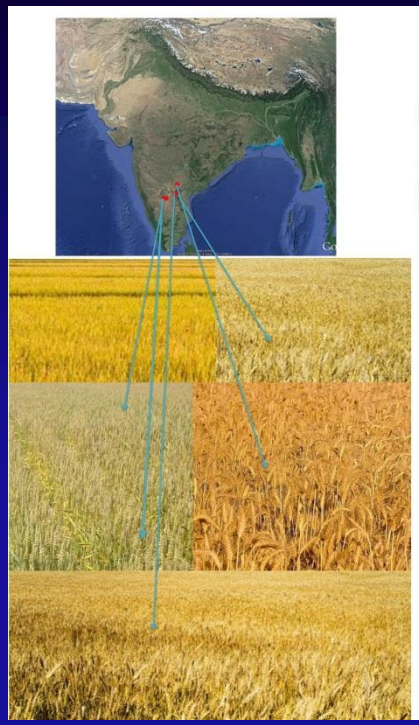
Wheat, Rice, Corn, and Cotton

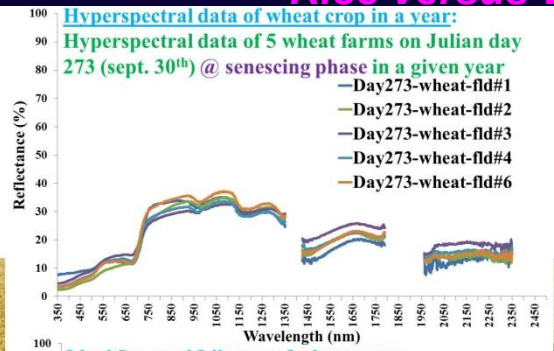


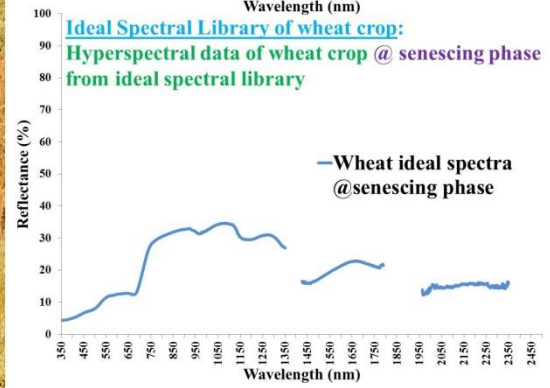
Hyperion data of crops illustrated for typical growth stages in the Uzbekistan study area. The Hyperion data cube shown here is from a small portion of one of the two Hyperion images. The Hyperion spectra of crops are gathered from different farm fields in the two images and their average spectra illustrated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

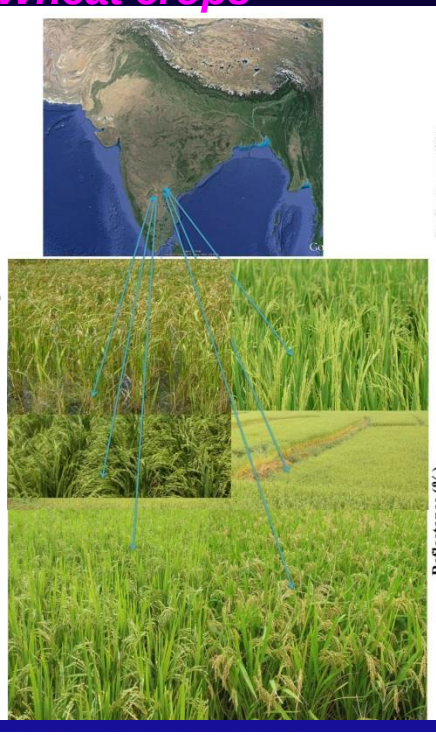
Hyperspectral Data of Agricultural Crops from Spectroradiometer: India

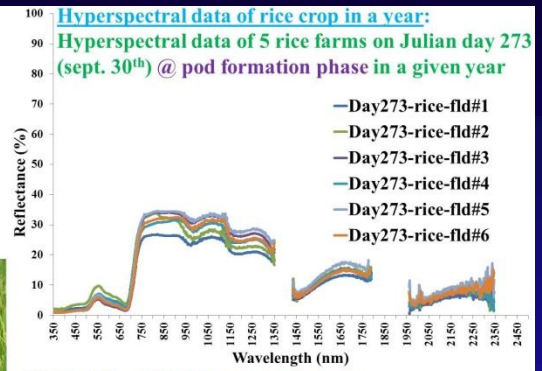
Rice versus Wheat crops

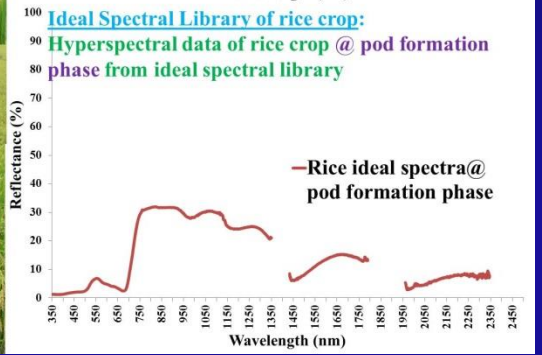


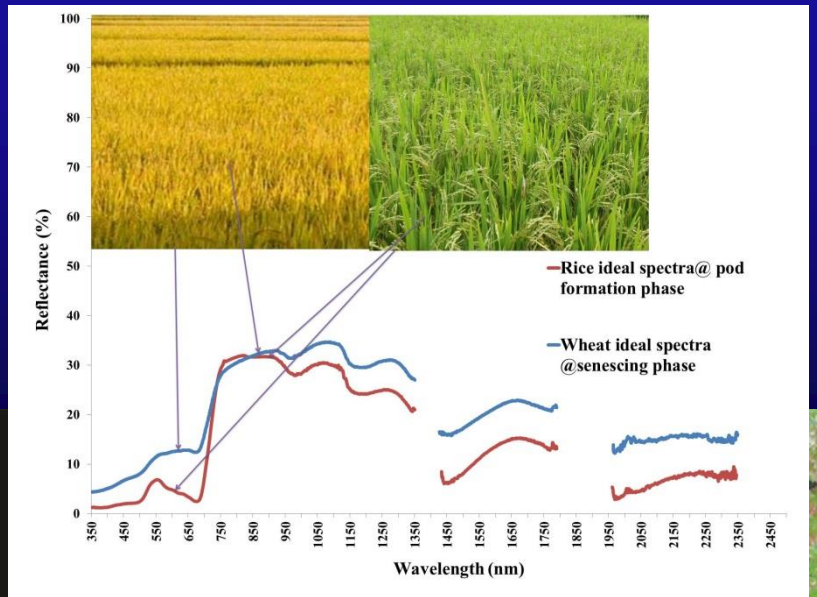












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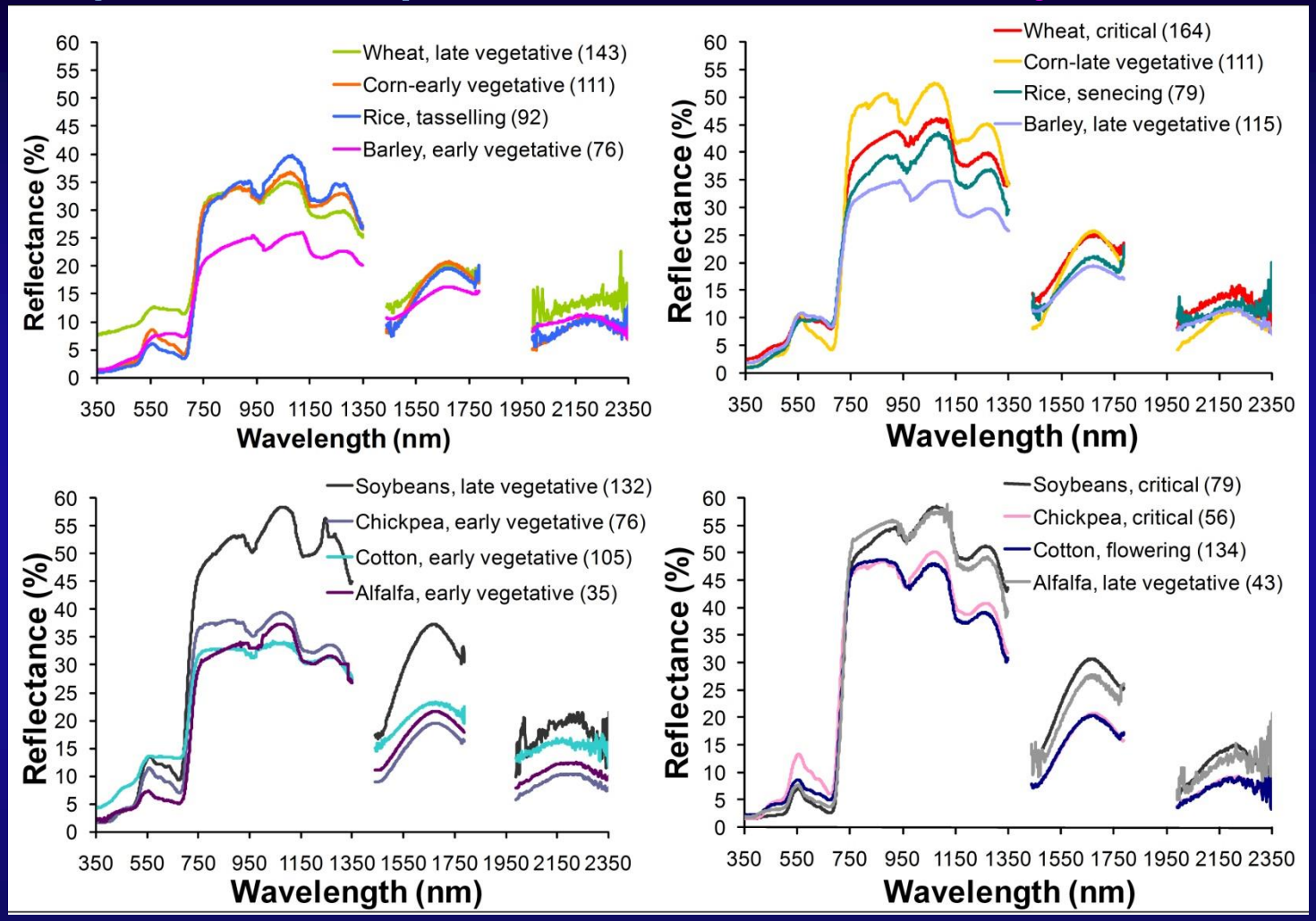
Hyperspectral Data of Agricultural Crops from EO-1 Hyperion: Worldwide

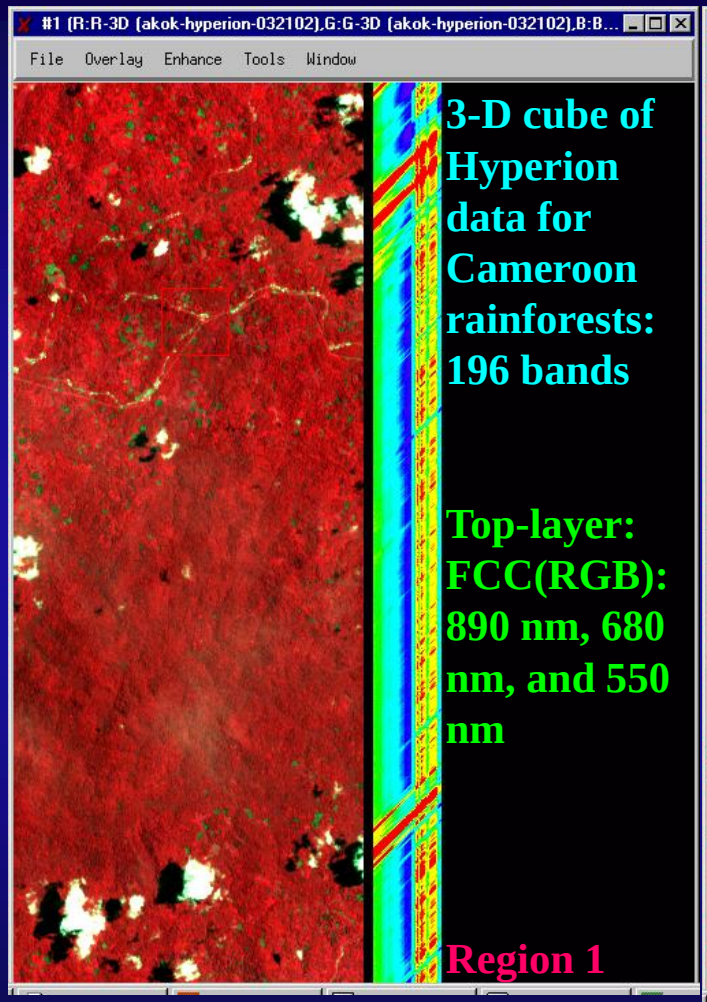
Major World Crops: *Wheat, Rice, Corn, Barley, Cotton, Alfalfa, Chickpea*

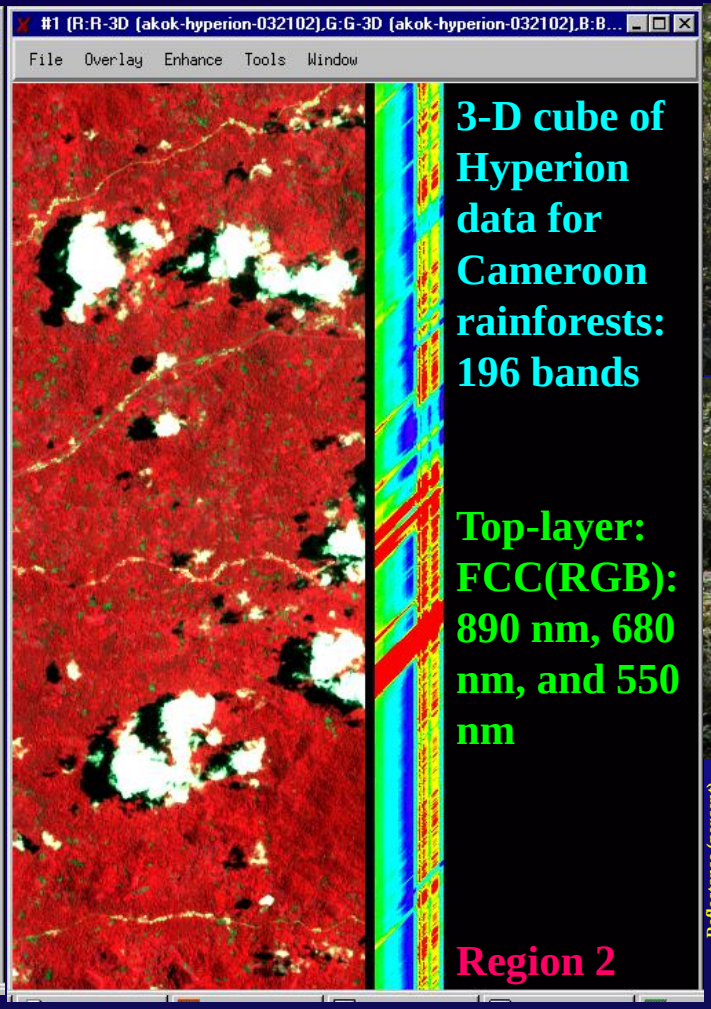


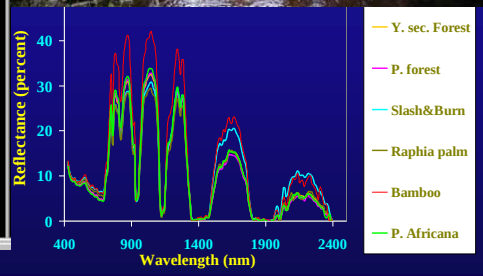
Cross-site hyperspectral spectroradiometer data. Cross-site mean (regardless of which study site (1-4, Table 2)) spectral plots of eight leading world crops in various growth stages. (A) Four crops at different growth stages; (B) same four crops as in A but in different growth stages; (C) four more crops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

Hyperspectral Data of Rainforest Vegetation from EO-1 Hyperion: Cameroun

Different Types of Vegetation in primary and secondary forests







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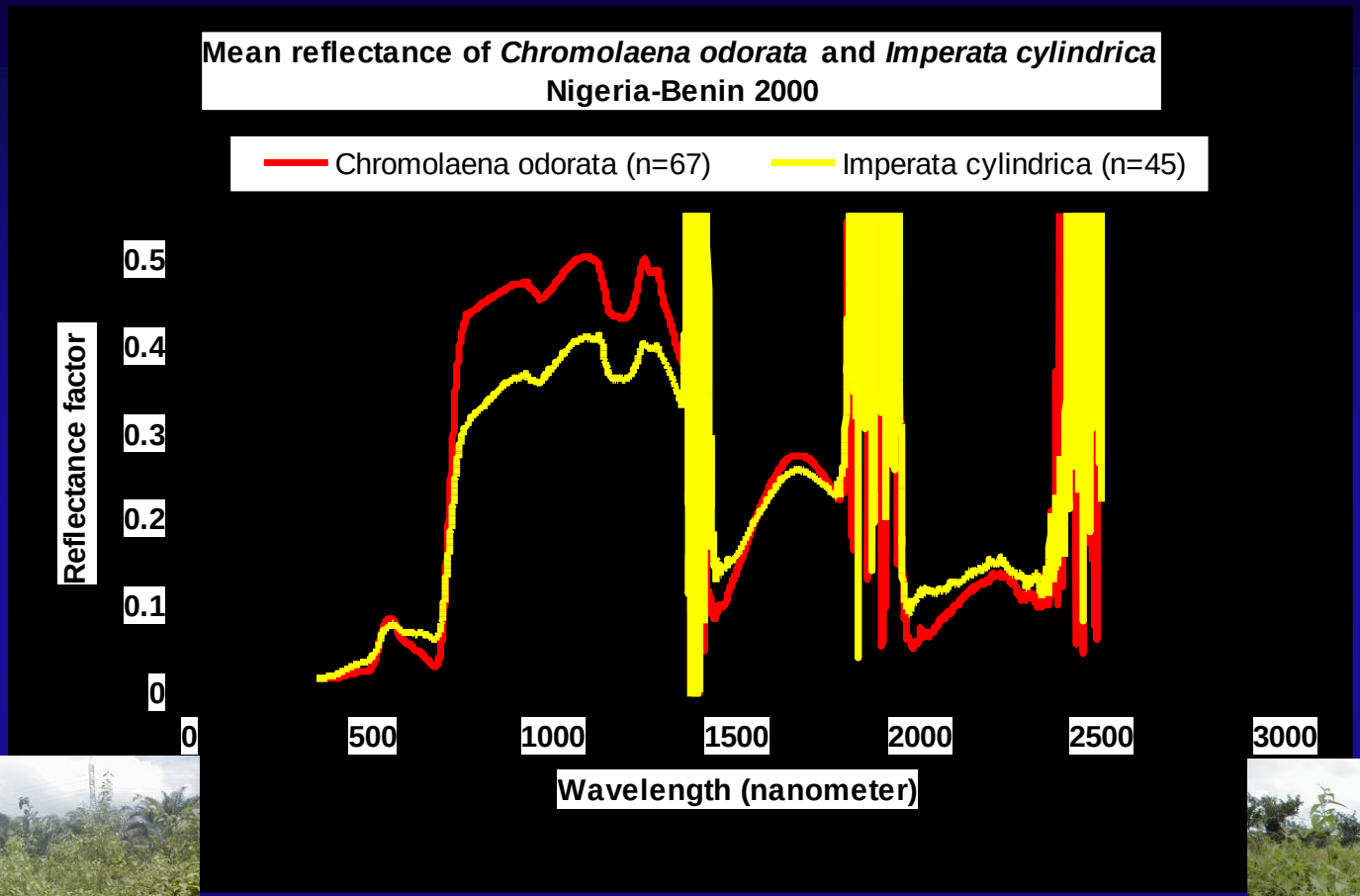
Hyperspectral Data of two Dominant Weeds from Spectroradiometer: Africa

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



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

U.S. Geological Survey
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Data Mining and Overcoming Hughes Phenomenon
(Curse of High Dimensionality of Data & overcoming data redundancy through Data Mining)

Hyperspectral Data (Imaging Spectroscopy data)

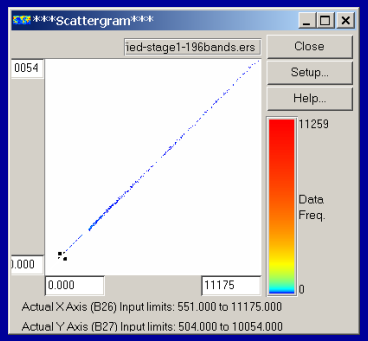
Not a Panacea!

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

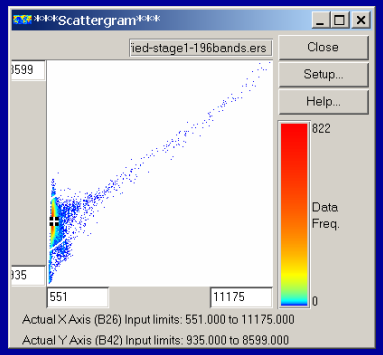
- data storage volume;
- data storage rate;
- downlink or transmission bandwidth;
- computing bottle neck in data analysis; and
- new algorithms for data utilization (e.g., atmospheric correction more complicated).

Data Mining Methods and Approaches in Vegetation Studies

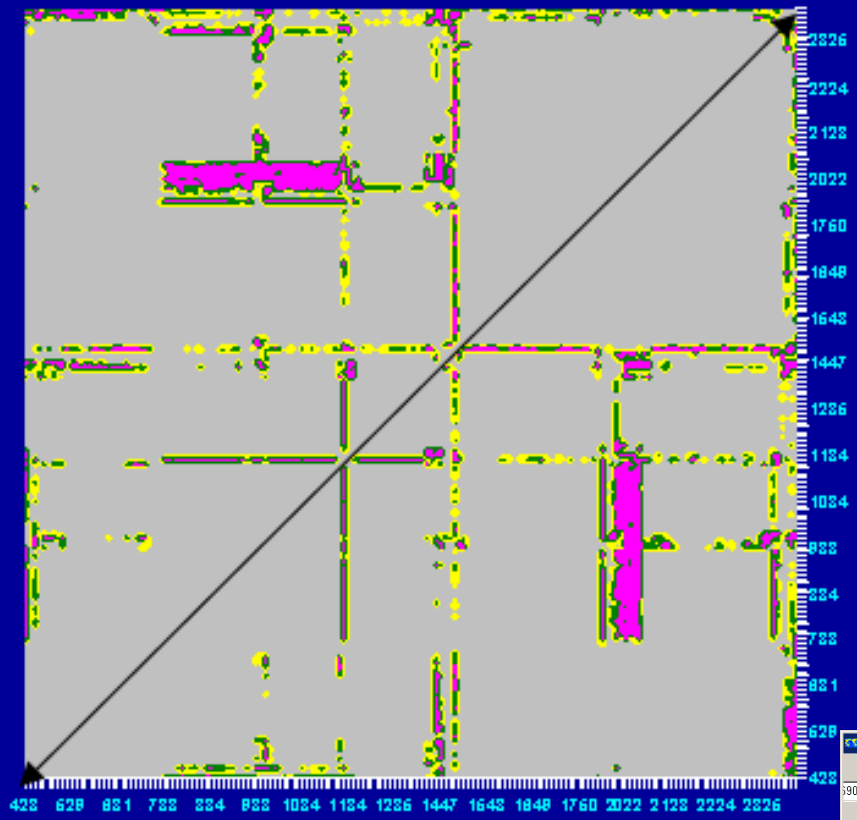
Lambda by Lambda R-square Contour Plots: Identifying Least Redundant Bands



Highly redundant: bands centered at 680 nm and 690 nm



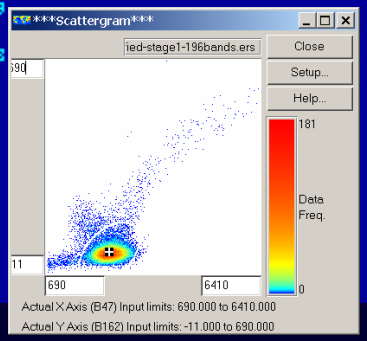
Significantly different: bands centered at 680 nm and 890 nm



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



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; FMIR;EMIR;MMIR;FM; 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						

Methods of Hyperspectral Data Analysis

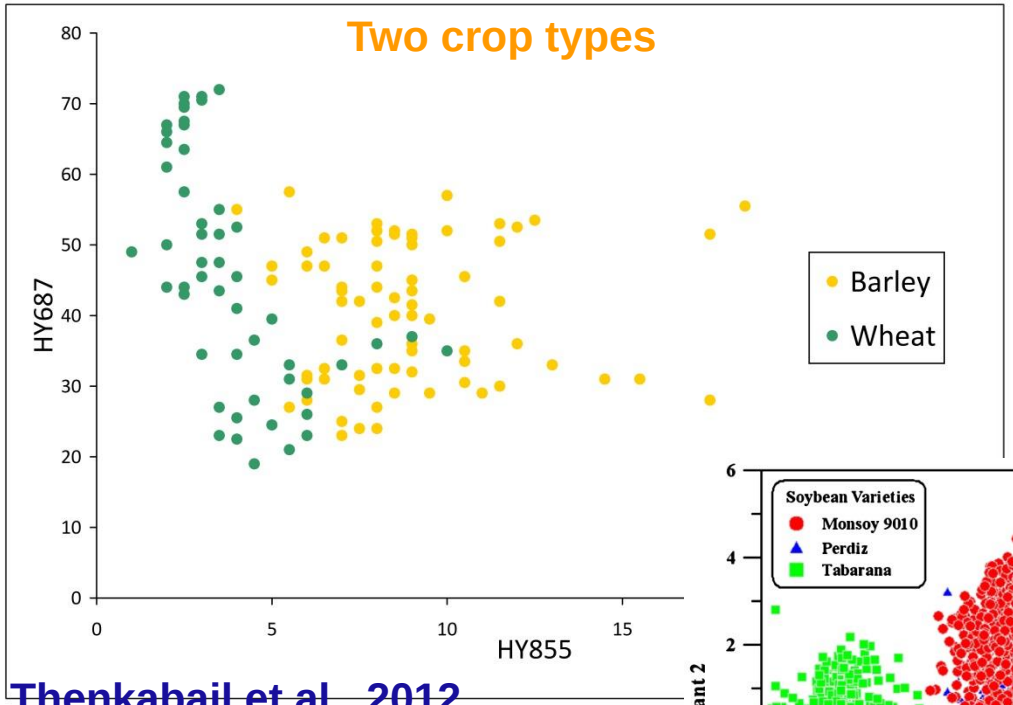
Class Separability

Agriculture and Vegetation

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

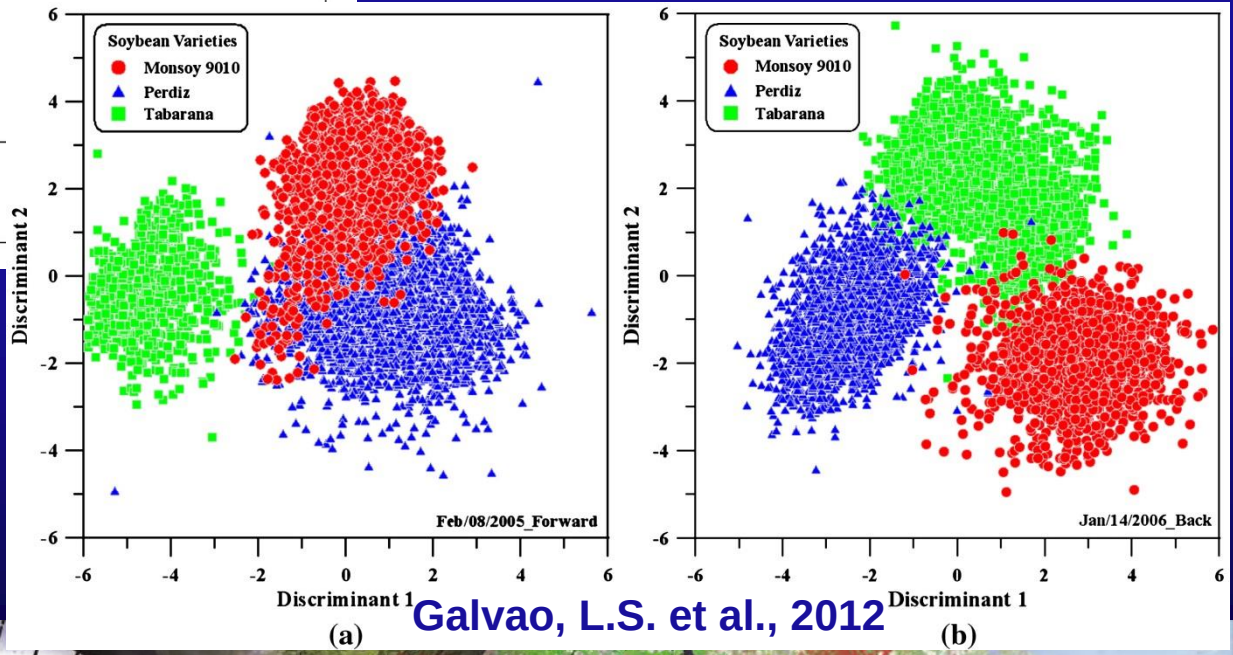
Hyperspectral Narrowband Study of Agricultural Crops

Methods of Hyperspectral Data Analysis



Thenkabail et al., 2012

Three soybean varieties

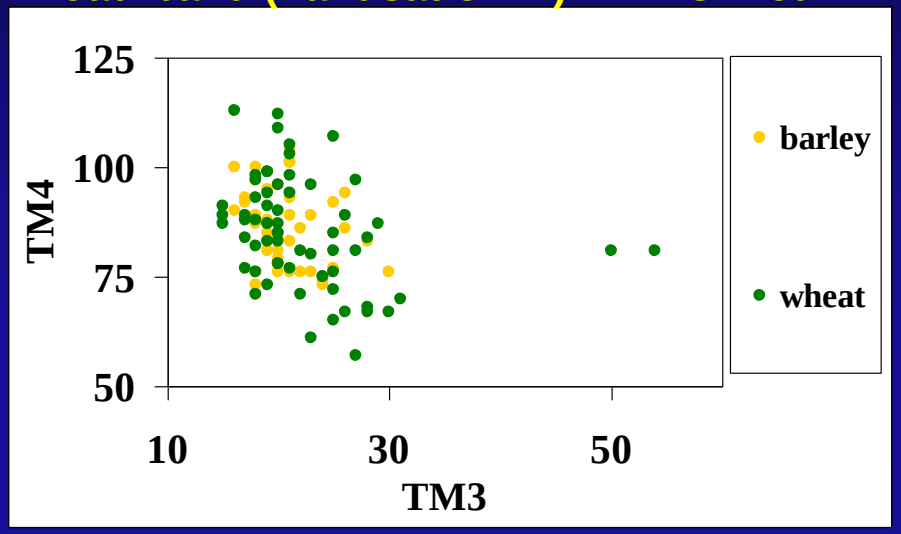


Galvao, L.S. et al., 2012

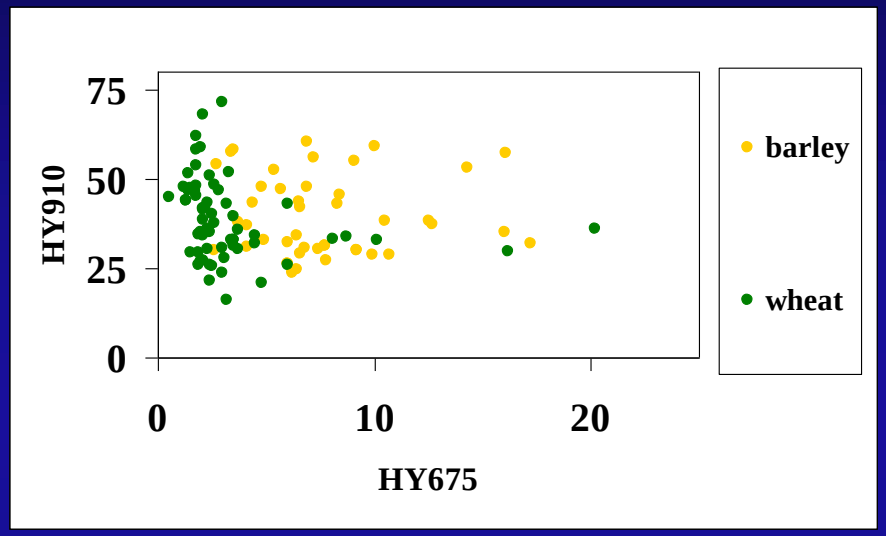
Discriminating\Separating Vegetation Types

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

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



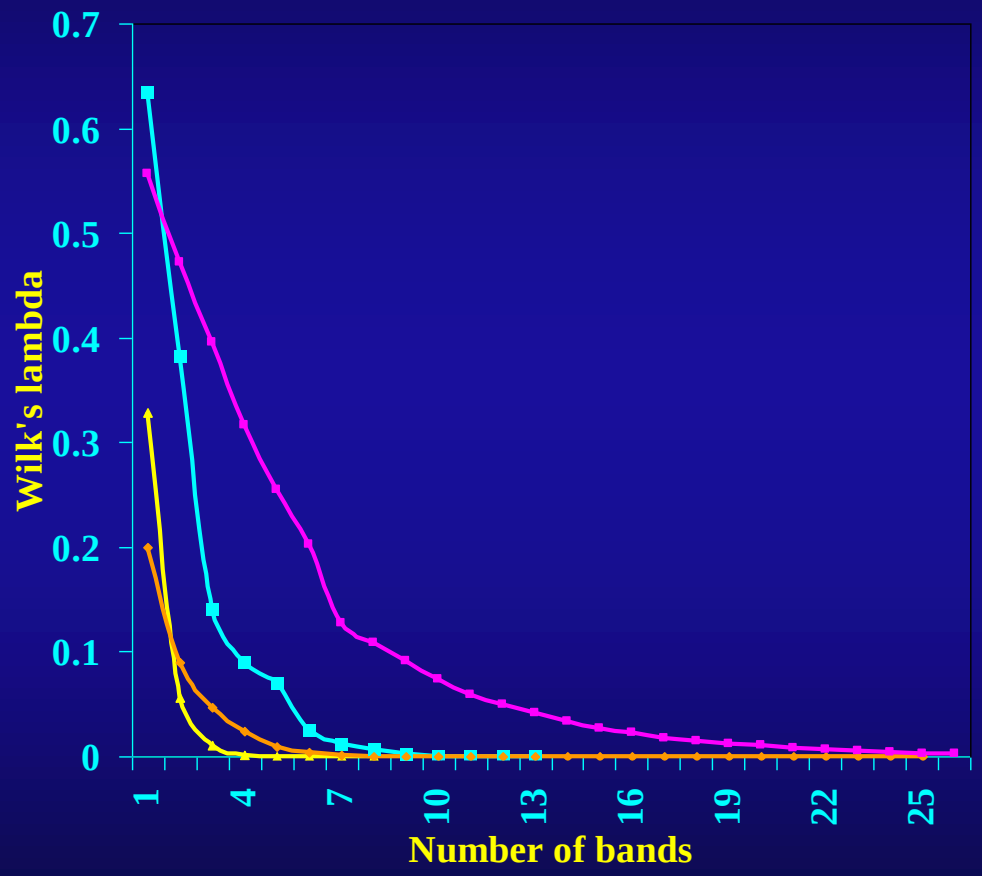
Narrow-band NIR vs. Red



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

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

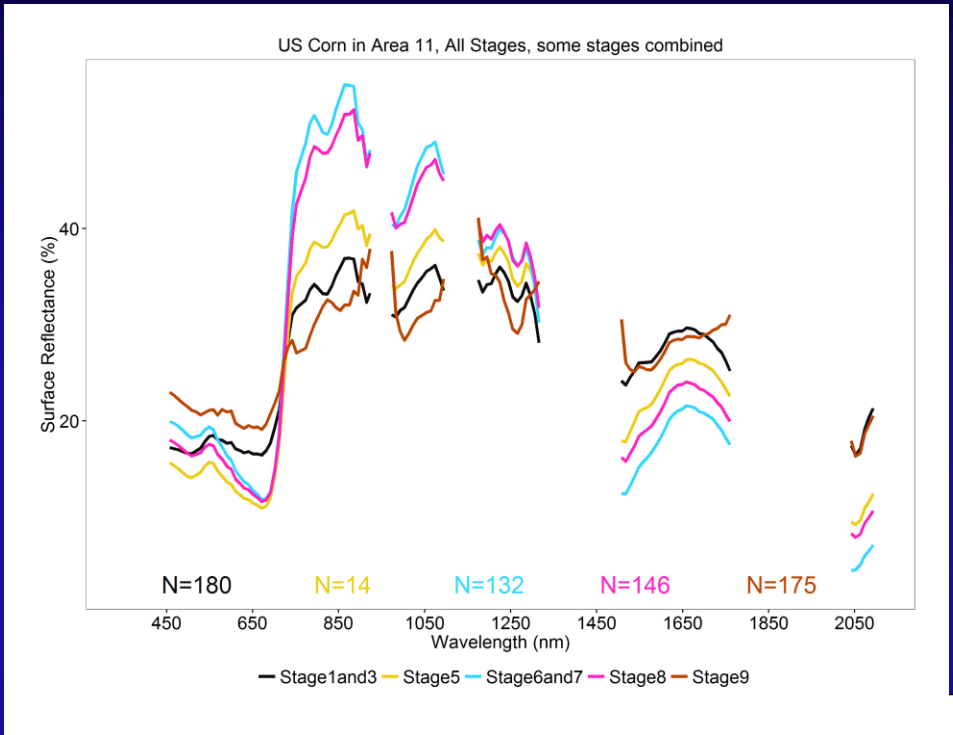


Lesser the Wilks' Lambda greater is the seperability. Note that beyond 10-20 wavebands Wilks' Lambda becomes asymptotic.

- **Fallow**
  1-3 yr vs. 3-5 yr vs. 5-8 yr
- **Primary forest**
  Pristine vs. degraded
- **Secondary forest**
  Young vs. mature vs. mixed
- **Primary + secondary forests + fallow areas**
  All above

Linear Discriminant Analysis

Corn, Areas 11, Stages Combined



Actual

Predicted	ZeroOneThree	Five	SixSeven	Eight	Nine	Total	User's Accuracy
ZeroOneThree	133	1	4	7	9	154	86
Five	1	6	1	3	0	11	55
SixSeven	8	0	63	16	1	88	72
Eight	8	0	34	84	1	127	66
Nine	0	0	0	5	134	139	96
Total	150	7	102	115	145	519	
Producer's Accuracy	89	86	62	73	92		81

Methods of Hyperspectral Data Analysis

Hyperspectral Vegetation Indices (HVIs)

Agriculture and Vegetation

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

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

Hyperspectral Vegetation Indices (HVI's)

Hyperspectral Two-band Vegetation Indices (HTBVI's)

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.

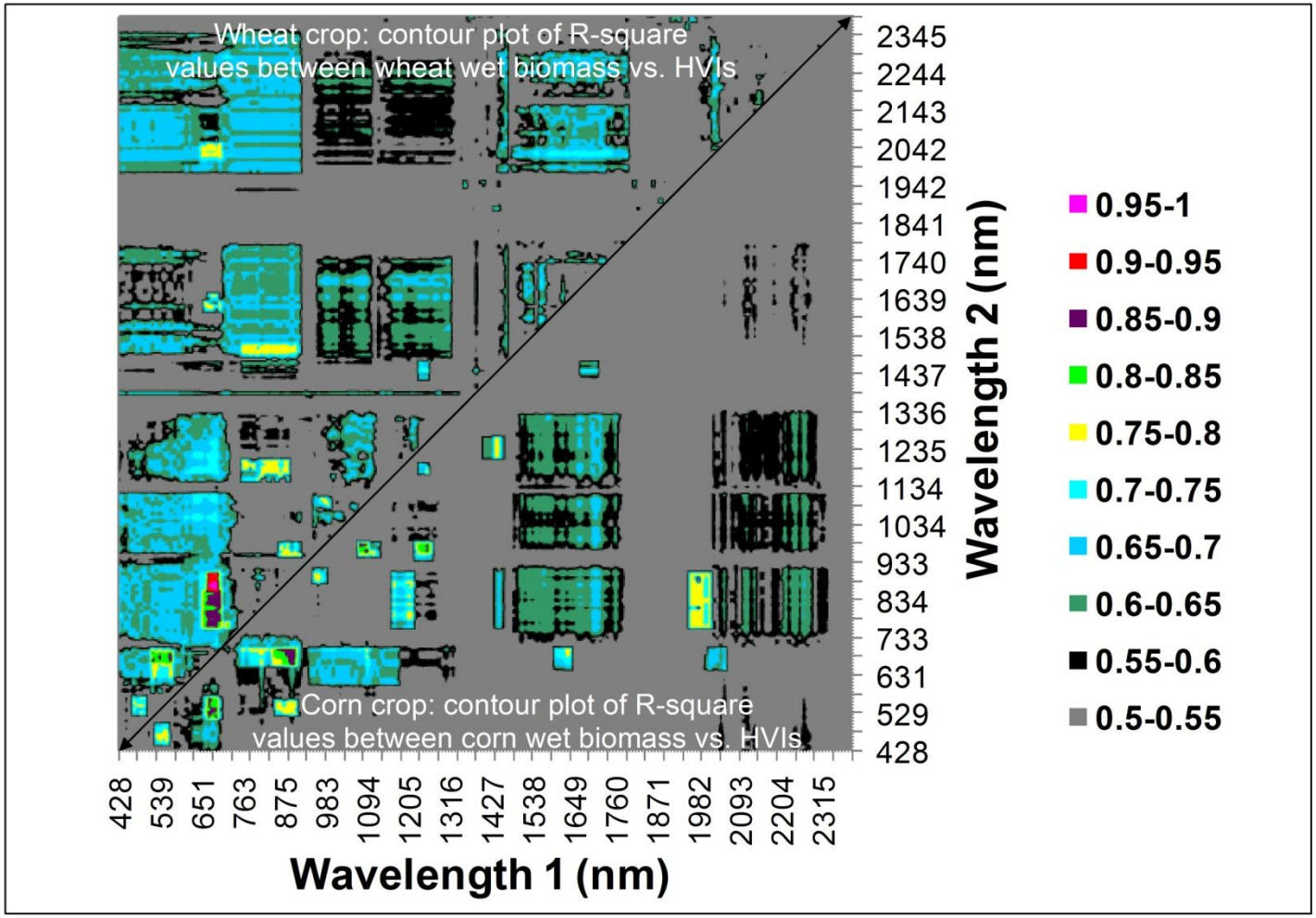
- where, i,j = 1, N, with N=number of narrow-bands= 157 (each band of 1 nm-wide spread over 400 nm to 2500 nm), R=reflectance of narrow-bands.

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.

Hyperspectral Vegetation Indices (HVI's): Agricultural Crops

Hyperspectral Two-band Vegetation Indices (HTBVI's)

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

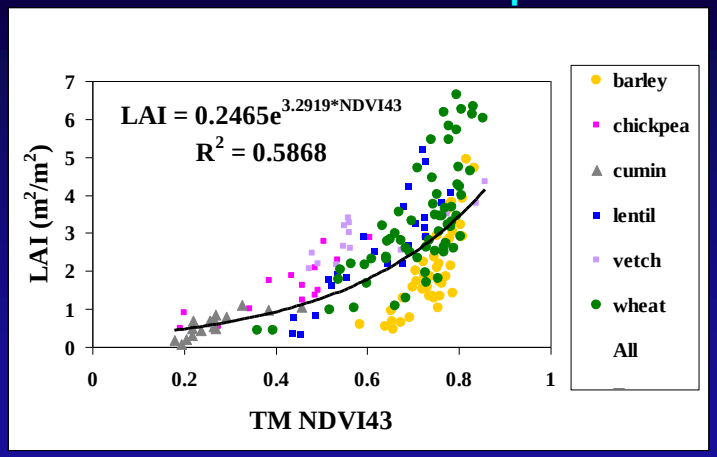


Contour plot of λ versus λ R^2- values for wavelength bands between two-band hyperspectral vegetation indices (HVIs) and wet biomass of wheat crop (above diagonal) and corn crop (below diagonal). The 242 Hyperion bands were reduced to 157 bands after eliminating uncalibrated bands and the bands in atmospheric 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.

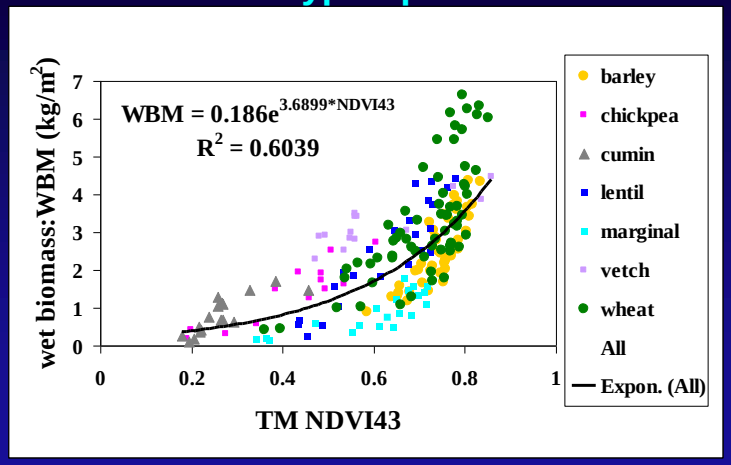
Hyperspectral Vegetation Indices (HVI's): Agricultural Crops

Hyperspectral Two-band Vegetation Indices (HTBVI's)

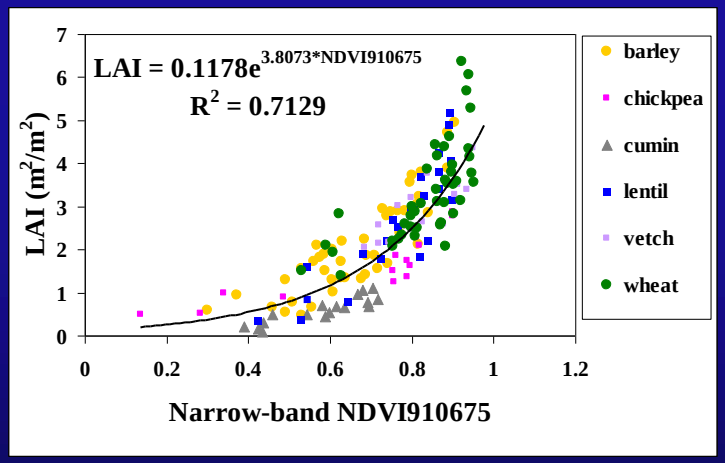
Multispectral Broadbands versus hyperspectral narrowbands



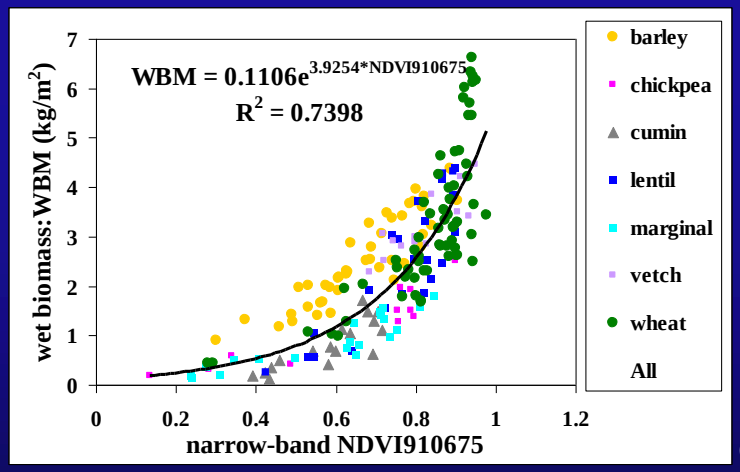
Broad-band NDVI43 vs. LAI



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.

Hyperspectral Vegetation Indices (HVI's)

Hyperspectral Multi-band Vegetation Indices (HMBVI's)

Best 1-band, 2-band, 3-band,…….best n-band HVI's

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

where, HMBVI = 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.

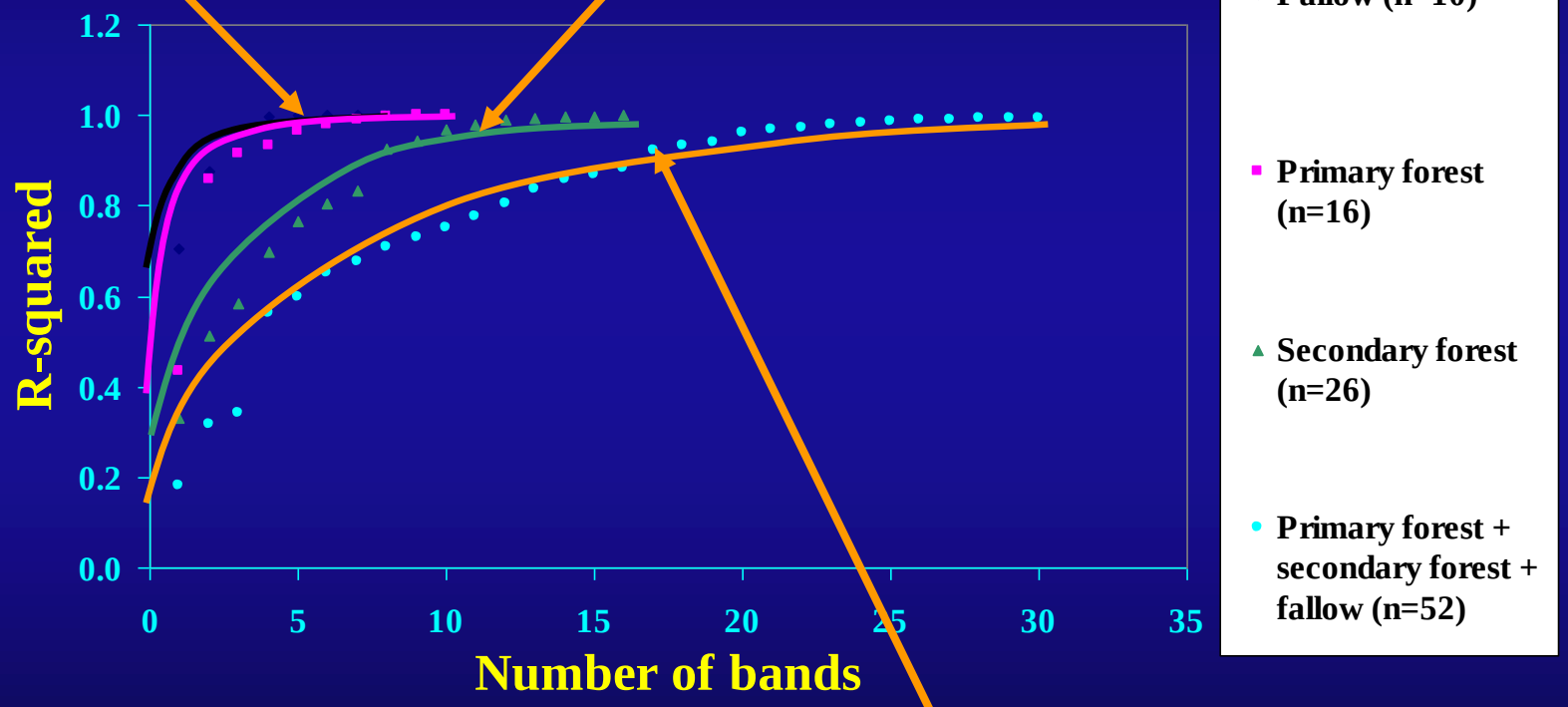
Hyperspectral Vegetation Indices (HVI's): Agricultural Crops

Hyperspectral Multi-band Vegetation Indices (HMBVI's)

Best 1-band, 2-band, 3-band,…….best n-band HVI's

<u>Note</u>: Increase in R^2 values beyond 6 bands is negligible

<u>Note</u>: Increase in R^2 values beyond 11 bands is negligible



<u>Note</u>: Increase in R^2 values beyond 17 bands is negligible

Hyperspectral Vegetation Indices (HVI's): Agricultural Crops

Hyperspectral Derivative Greenness Vegetation Indices (HDGVI's)

Best 1-band, 2-band, 3-band,…….best n-band HVI's

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.

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

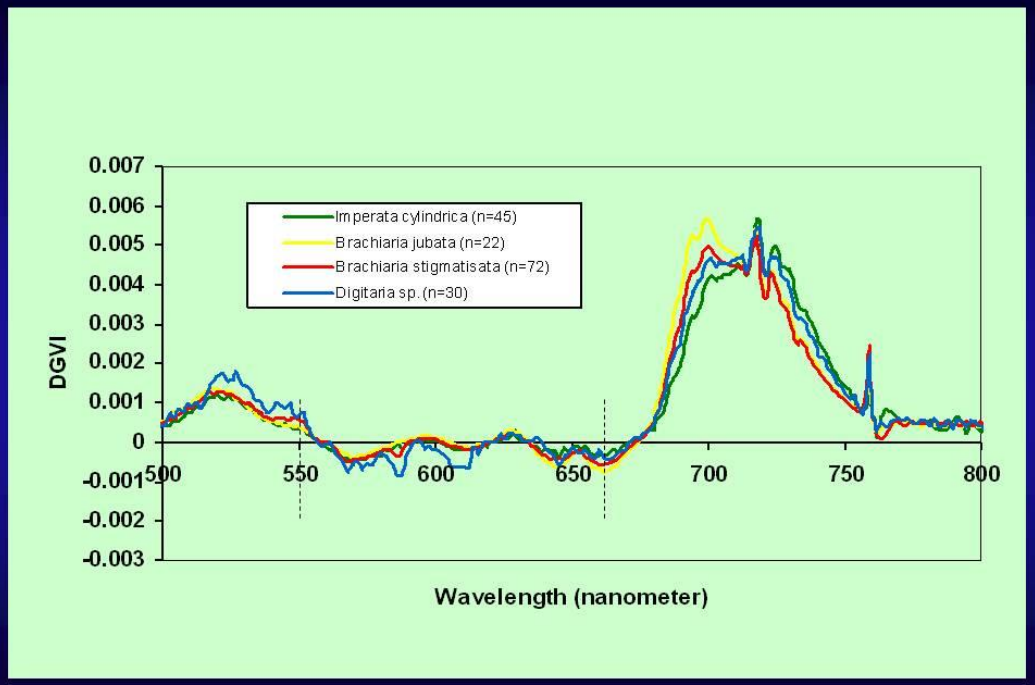
Where, I and j are band numbers,

λ = center of wavelength,

$\lambda_1 = 0.626\ \mu m$,

$\lambda_n = 0.795\ \mu m$,

ρ' = first derivative reflectance.



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

Methods of Hyperspectral Data Analysis

Advances Made &

Knowledge Gained over Last 50- years

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

Overcoming Hughes' Phenomenon by Leaving out Redundant Bands

1. Overcoming the Hughes phenomenon (or the curse of high dimensionality of hyperspectral data)

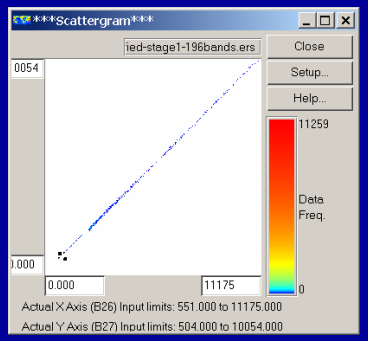
Reduce data volumes significantly by eliminating redundant bands and focusing on the most valuable hyperspectral narrowbands to study agricultural crops and vegetation.

Note:

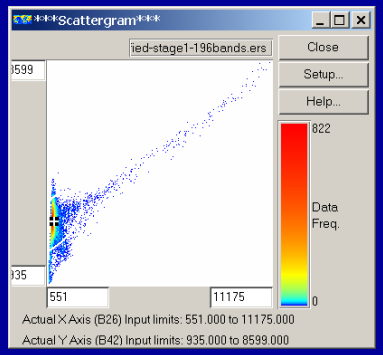
A. Optimal hyperspectral narrowbands (HNBs). Leave out redundant bands;

B. Overcoming Hughes' Phenomenon: If the number of bands remained high, the number of observations required to train a classifier increases exponentially to maintain classification accuracies. Data volumes are reduced through data mining methods such as feature selection (e.g., principal component analysis, derivative analysis, wavelets), lambda by lambda correlation plots, and vegetation indices. Data mining methods lead to: (a) reduction in data dimensionality, (b) reduction in data redundancy, and (c) extraction of unique information.

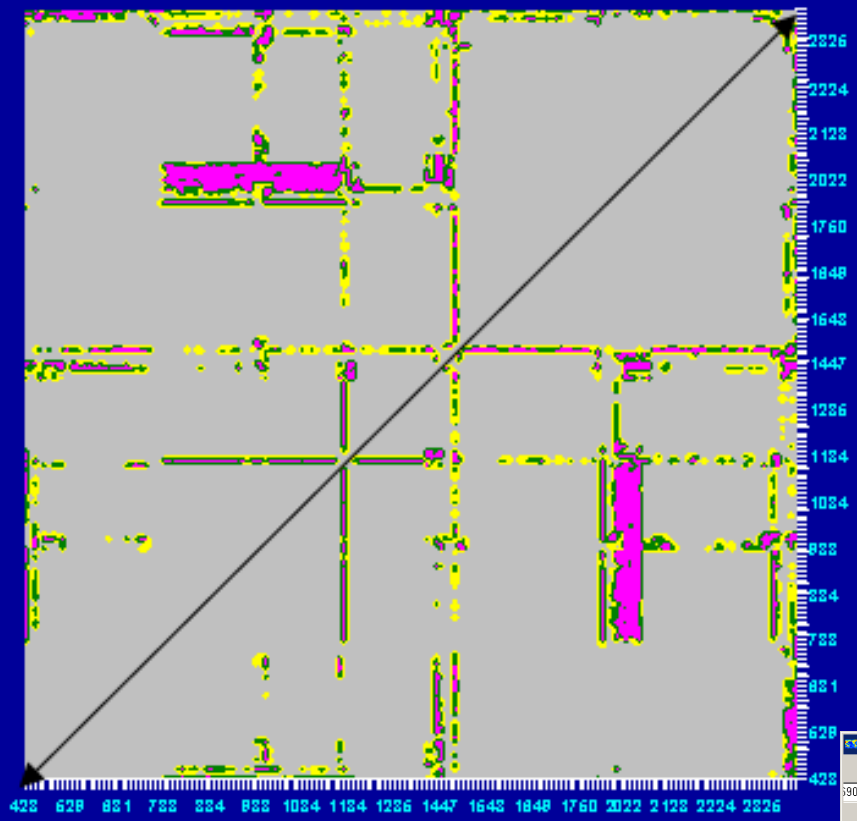
Overcoming Hughes' Phenomenon by Leaving out Redundant Bands



Highly redundant: bands centered at 680 nm and 690 nm



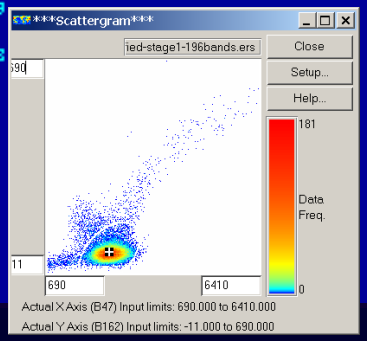
Significantly different: bands centered at 680 nm and 890 nm



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



Distinctly different: bands centered at 920 nm and 2050 nm

Selecting Targeted Optimal Hyperspectral Narrowbands (HNB's) by Comprehensive Research

2. Narrowbands targeted to study specific vegetation biophysical and biochemical variable:

Each waveband in Table is uniquely targeted to study specific vegetation biophysical, and biochemical properties and/or captures specific events such as plant stress.

Note:

A. Targeted hyperspectral narrowbands (HNBs) in previous 3 slides: selecting Optimal bands, eliminating redundant bands.

2. Examples of targeted HNBs: For example:

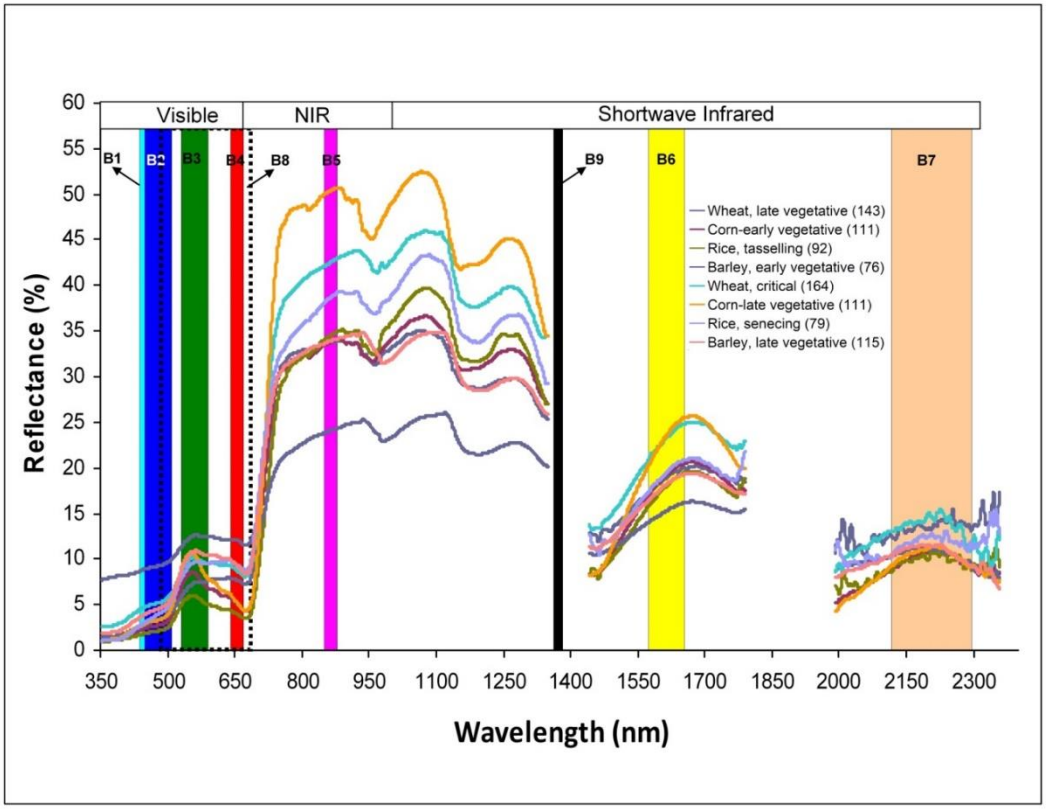
i. waveband centered at 550 nm provided excellent sensitivity to plant nitrogen,

ii. waveband centered at 515 nm is best for pigments (carotenoids, anthocyanins), wavebands centered at 970 or 1245 nm was ideal to study plant moisture fluctuations, and

iii. Lignin, cellulose, protein, and nitrogen have relatively low reflectance and strong absorption in SWIR bands by water that masks other absorption features.

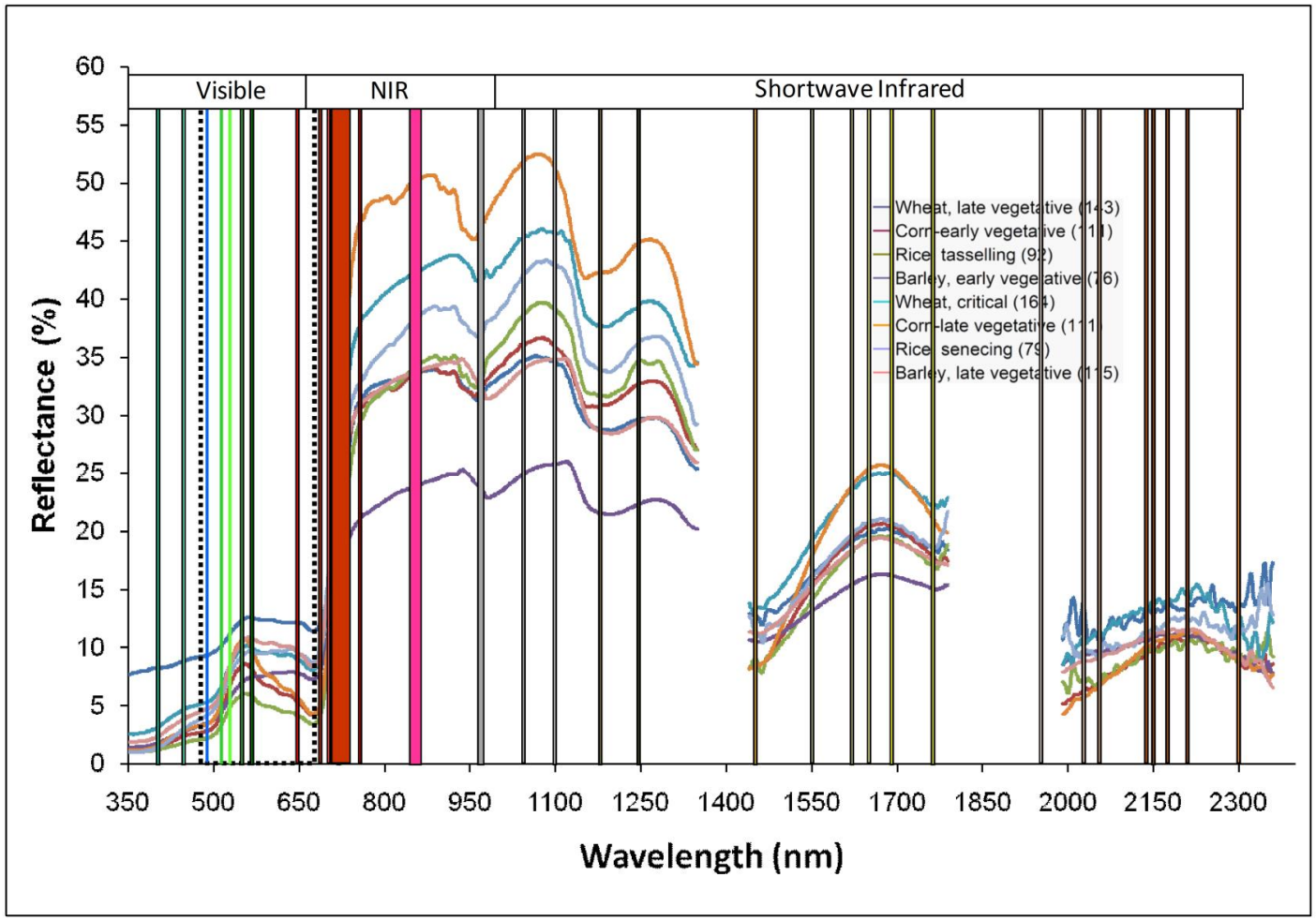
Hyperspectral Remote Sensing of Crops and Vegetation: Knowledge Gained Over Last 50-Years

Selecting Targeted Optimal Hyperspectral Narrowbands (HNB's) by Comparing Multispectral broadbands versus Hyperspectral Narrowbands



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.

Selecting Targeted Optimal Hyperspectral Narrowbands (HNB's) by Comparing Multispectral broadbands versus Hyperspectral Narrowbands



Hyperspectral Remote Sensing of Crops and Vegetation: Knowledge Gained Over Last 50-Years

Selecting Targeted Optimal Hyperspectral Narrowbands (HNB's) by Selecting Waveband Centers, Waveband Widths, and Targeted Application in 400-2500 nm

Table 2. Optimal (non-redundant) hyperspectral narrowbands to study vegetation and agricultural crops[1,2,3] [modified and adopted from Thenkabail et al., 2014, 2013, 2011, 2004a, 2004b, 2002, 2000].

Waveband number #	Waveband range λ	Waveband center λ	Waveband width Δλ	Importance and physical significance of waveband in vegetation and cropland studies
A. Ultrviolet				
1	373-377	375	5	fPAR, leaf water: fraction of photosynthetically active radiation (fPAR), leaf water content
B. Blue bands				
2	403-407	405	5	Nitrogen, Senescing: sensitivity to changes in leaf nitrogen. reflectance changes due to pigments is moderate to low. Sensitive to senescing (yellow and yellow green leaves).
3	491-500	495	10	Carotenoid, Light use efficiency (LUE), Stress in vegetation: Sensitive to senescing and loss of chlorophyll\browning, ripening, crop yield, and soil background effects
C. Green bands				
4	513-517	515	5	Pigments (Carotenoid, Chlorophyll, anthocyanins), Nitrogen, Vigor: positive change in reflectance per unit change in wavelength of this visible spectrum is maximum around this green waveband
5	530.5-531.5	531	1	Light use efficiency (LUE), Xanophyll cycle, Stress in vegetation, pest and disease: Senescing and loss of chlorophyll\browning, ripening, crop yield, and soil background effects
6	546-555	550	10	Chlorophyll: Total chlorophyll; Chlorophyll/carotenoid ratio, vegetation nutritional and fertility level; vegetation discrimination; vegetation classification
7	566-575	570	10	Pigments (Anthrocyanins, Chlorophyll), Nitrogen: negative change in reflectance per unit change in wavelength is maximum as a result of sensitivity to vegetation vigor, pigment, and N.
D. Red bands				
8	676-685	680	10	Biophysical quantities and yield: leaf area index, wet and dry biomass, plant height, grain yield, crop type, crop discrimination
E. Red-edge bands				
9	703-707	705	5	Stress and chlorophyll: Nitrogen stress, crop stress, crop growth stage studies
10	718-722	720	5	Stress and chlorophyll: Nitrogen stress, crop stress, crop growth stage studies
11	700-740	700-740	700-740	Chlorophyll, senescing, stress, drought: first-order derivative index over 700-740 nm has applications in vegetation studies (e.g., blue-shift during stress and red-shift during healthy growth)
F. Near infrared (NIR) bands				
12	841-860	850	20	Biophysical quantities and yield: LAI, wet and dry biomass, plant height, grain yield, crop type, crop discrimination, total chlorophyll
13	886-915	900	20	Biophysical quantities, Yield, Moisture index: peak NIR reflectance. Useful for computing crop moisture sensitivity index, NDVI; biomass, LAI, Yield.

Thenkabail et al. 2015

……Continued in next slide

Hyperspectral Remote Sensing of Crops and Vegetation: Knowledge Gained Over Last 50-Years

Selecting Targeted Optimal Hyperspectral Narrowbands (HNB's) by Selecting Waveband Centers, Waveband Widths, and Targeted Application in 400-2500 nm

G. Near infrared (NIR) bands				
14	961-980	970	20	Plant moisture content Center of moisture sensitive "trough"; water band index, leaf water, biomass;
H. Far near infrared (FNIR) bands				
15	1073-1077	1075	5	Biophysical and biochemical quantities: leaf area index, wet and dry biomass, plant height, grain yield, crop type, crop discrimination, total chlorophyll, anthocyanin, carotenoids
16	1178-1182	1080	5	Water absorption band
17	1243-1247	1245	5	Water sensitivity: water band index, leaf water, biomass. Reflectance peak in 1050-1300 nm.
I. Early short-wave infrared (ESWIR) bands				
18	1448-1532	1450	5	Vegetation classification and discrimination: ecotype classification; plant moisture sensitivity. Moisture absorption trough inearly short wave infrared (ESWIR)
19	1516-1520	1518	5	Moisture and biomass: A point of most rapid rise in spectra with unit change in wavelength in SWIR. Sensitive to plant moisture.
20	1648-1652	1650	5	Heavy metal stress, Moisture sensitivity: Heavy metal stress due to reduction in Chlorophyll. Sensitivity to plant moisture fluctuations in ESWIR. Use as an index with 1548 or 1620 or 1690 nm..
21	1723-1727	1725	5	Lignin, biomass, starch, moisture: sensitive to lignin, biomass, starch. Discrimiating crops and vegetation.
J. Far short-wave infrared (FSWIR) bands				
22	1948-1952	1950	5	Water absorption band: highest moisture absorption trough in FSWIR. Use as an index with any one of 2025 nm, 2133 nm, and 2213 am. Affected by noise at times.
23	2019-2027	2023	8	Litter (plant litter), lignin, cellulose: litter-soil differentiation: moderate to low moisture absorption trough in FSWIR. Use as an index with any one of 2025 nm, 2133 nm, and 2213 am.
24	2131-2135	2133	5	Litter (plant litter), lignin, cellulose: typically highest refectivity in FSWIR for vegetation. Litter-soil differentiation
25	2203-2207	2205	5	Litter, lignin, cellulose, sugar, startch, protein; Heavy metal stress: typically, second highest reflectivity in FSWIR for vegetation. Heavy metal stress due to reduction in Chlorophyll
26	2258-2266	2262	8	Moisture and biomass: moisture absorption trough in far short-wave infrared (FSWIR). A point of most rapid change in slope of spectra based on land cover, vegetation type, and vigor.
27	2293-2297	2295	5	Stress: sensitive to soil background and plant stress
28	2357-2361	2359	5	Cellulose, protein, nitrogen: sensitive to crop stress, lignin, and starch
Note:				
1 = most hyperspectral narrowbands (HNBs)_ that adjoin one another are highly correlated for a given application. Hence from a large number of HNBs, these non-redundant (optimal) bands are selected				
2 = these optimal HNBs are for studying vegetation and agricultural crops. When we use some or all of these wavebands, we can attain highest possible classification accuracies in classifying vegetation categories or crop types				
3 = wavebands selected here are based on careful evaluation of large number of studies.				

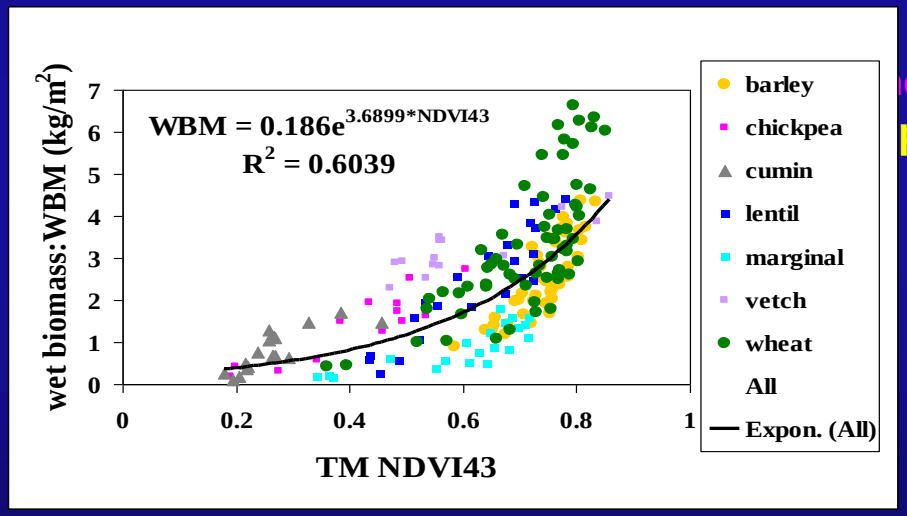
Thenkabail et al. 2015

……Continued from previous slide

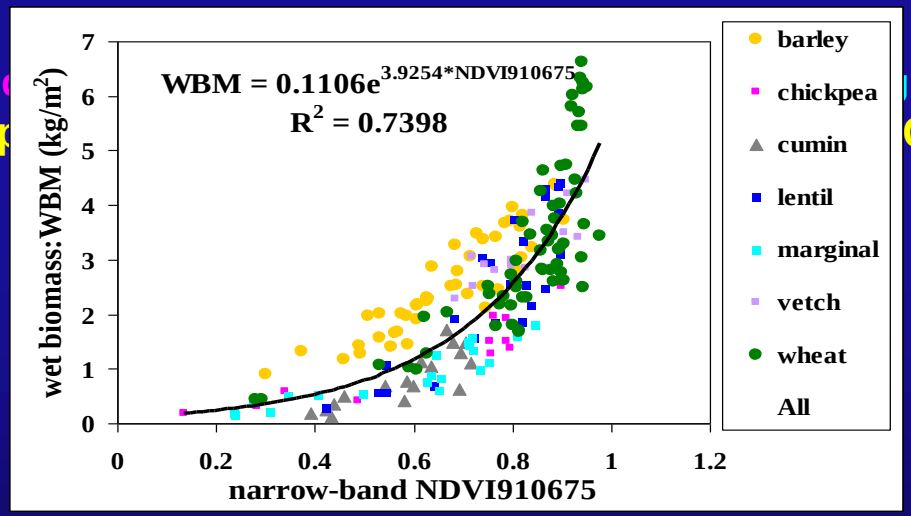
Developing Hyperspectral Vegetation Indices (HVI's) through Best Hyperspectral Two-band Vegetation Indices (HTBVI's): Illustration

3. HVIs for Improved models of agricultural crops and vegetation biophysical and biochemical variables

HVIs provide significantly improved models of crop and vegetation quantities such as biomass, LAI, NPP, leaf nitrogen, chlorophyll, carotenoids, and anthocyanins.



Broad-band NDVI43 vs. WBM



Narrow-band NDVI43 vs. WBM

Hyperspectral Remote Sensing of Crops and Vegetation: Knowledge Gained Over Last 50-Years

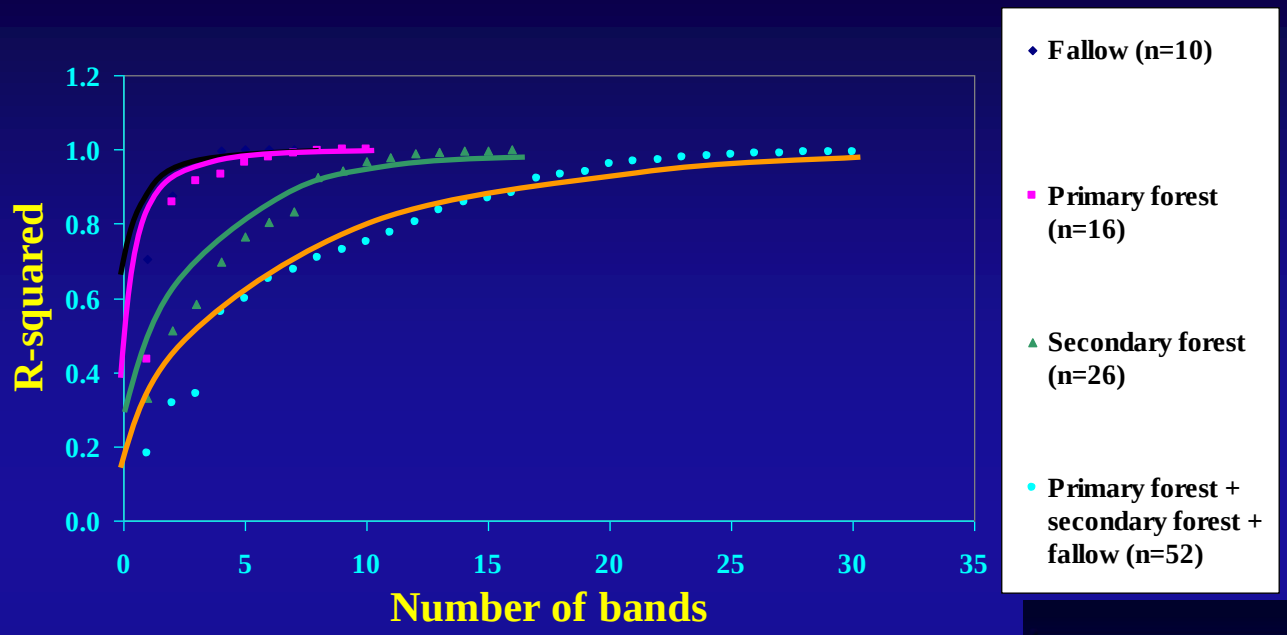
Developing Hyperspectral Vegetation Indices (HVI's) through Best Hyperspectral Two-band Vegetation Indices (HTBVI's)

Band number (#)	Hyperspectral narrowband (λ1)	Bandwidth (Δλ1)	Hyperspectral narrowband (λ2)	Bandwidth (Δλ2)	Hyperspectral vegetation index (HVI)	Best index under each catogory
I. Hyperspectral biomass and structural indices (HBSIs) [to best study biomass, LAI, palnt height, and grain yield]						
HBSI1	855	20	682	5	(855-682)/(855+682)	HBSI: Hyperspectral biomass and structural index
HBSI2	910	20	682	5	(910-682)/(910+682)	
HBSI3	550	5	682	5	(550-682)/(550+682)	
II. Hyperspectral biochemical indices (HBCIs) [pigments like carotenoids, anthocyanins as well as Nitrogen, chlorophyll]						
HBCI8	550	5	515	5	(550-515)/(550+515)	HBCI: Hyperspectral biochemical index
HBCI9	550	5	490	5	(550-490)/(550+490)	
III. Hyperspectral Red-edge indices (HREIs) [to best study plant stress, drought]						
HREI14	700-740	40	first-order derivative integrated over red-edge (700-740 nm)			HREI: Hyperspectral red-edge index
HREI15	855	5	720	5	(855-720)/(855+720)	
IV. Hyperspectral water and moisture indices (HWMIs) [to best study plant water and mosture]						
HWMI17	855	20	970	10	(855-970)/(855+970)	HWMI: Hyperspectral water and moisture index
HWMI18	1075	5	970	10	(1075-970)/(1075+970)	
HWMI19	1075	5	1180	5	(1075-1180)/(1075+1180)	
HWMI20	1245	5	1180	5	(1245-1180)/(1245+1180)	
V. Hyperspectral Light-use efficiency Index (HLEI)[to best study light use efficiency or LUE]						
HLUE24	570	5	531	1	(570-531)/(570+531)	HLEI: Hyperspectral light-use efficiency index
VI. Hyperspectral legnin cellulose index (HLCI) [to best study plant legnin, cellulose, and plant residue]						
HLCI25	2205	5	2025	1	(2205-2025)/(2205+2025)	HLCI: Hyperspectral legnin cellulose index

Hyperspectral Remote Sensing of Crops and Vegetation: Knowledge Gained Over Last 50-Years

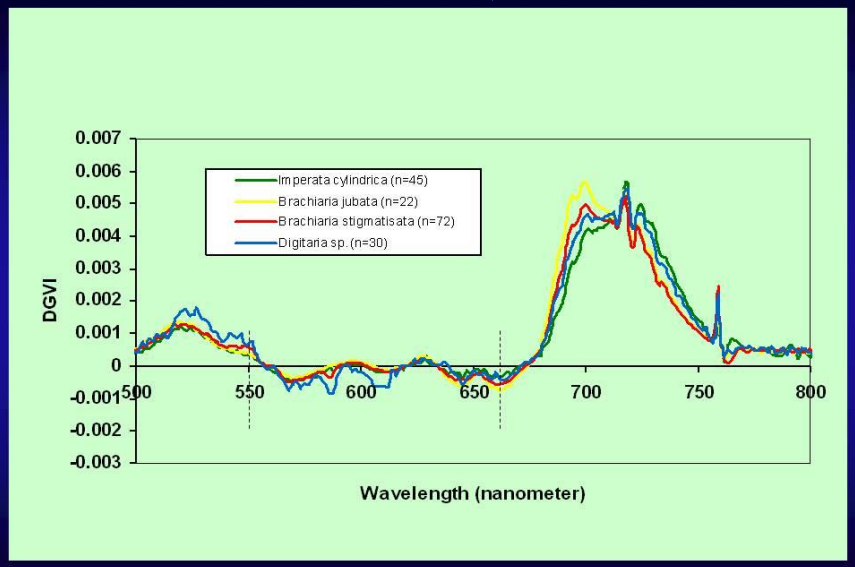
Developing Hyperspectral Vegetation Indices (HVI's) through

Best Hyperspectral Multi-band Vegetation Indices (HMBVI's), HDGVI's and so on



Hyperspectral Multi-band Vegetation Indices (HMBVI's)

Hyperspectral Multi-band Vegetation Indices (HMBVI's)



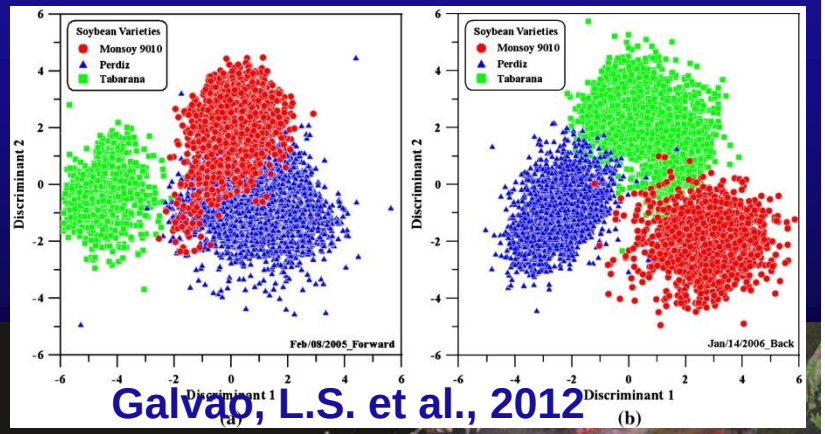
Crop Type and other Characteristic Separability through

Classifications, Discriminant Analysis

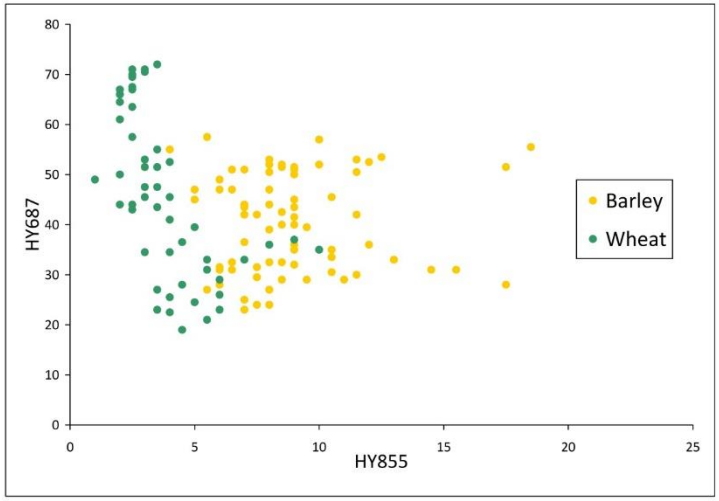
4. Distinct separation of vegetation types or species

Separating vegetation specific narrowbands, often, help discriminate two crop types or their variables distinctly when compared with broadbands.

Predicted	Actual: ZeroOneThree	Five	SixSeven	Eight	Nine	Total	User's Accuracy
ZeroOneThree	133	1	4	7	9	154	86
Five	1	6	1	3	0	11	55
SixSeven	8	0	63	16	1	88	72
Eight	8	0	34	84	1	127	66
Nine	0	0	0	5	134	139	96
Total	150	7	102	115	145	519	
Producer's Accuracy	89	86	62	73	92		81

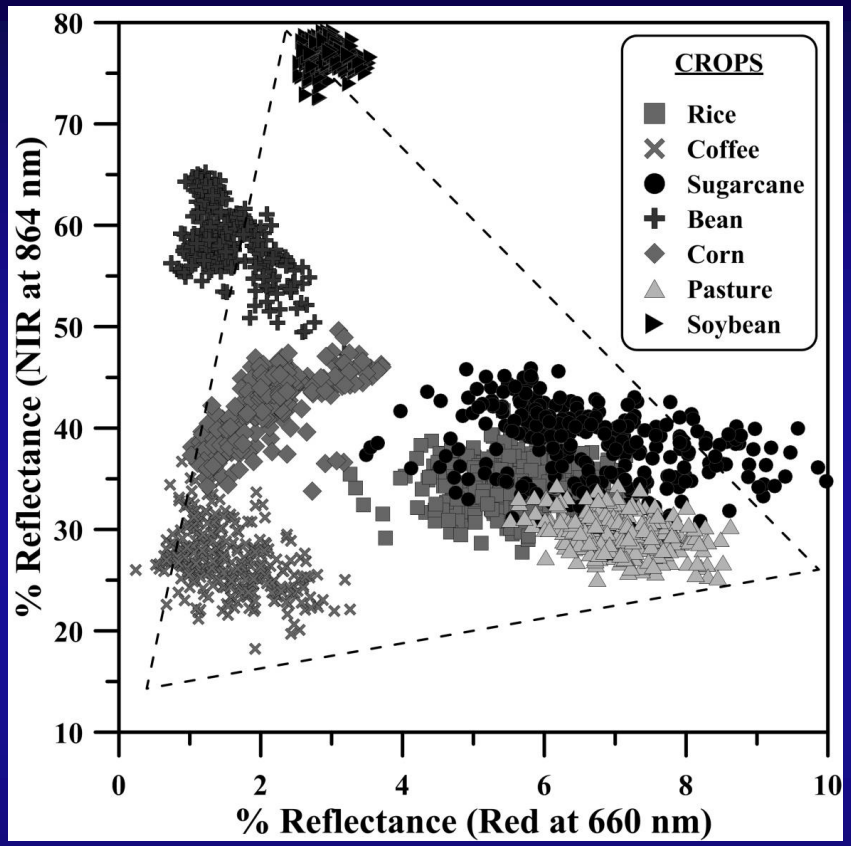


Galvao, L.S. et al., 2012

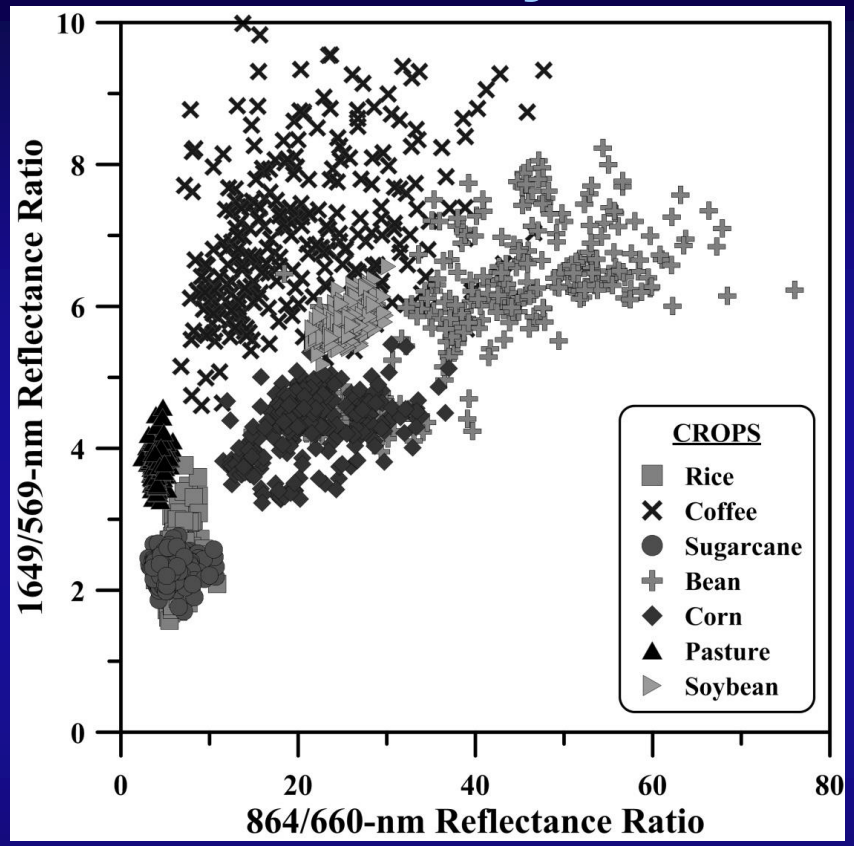


Crop Type and other Characteristic Separability through

Classifications, Discriminant Analysis



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.

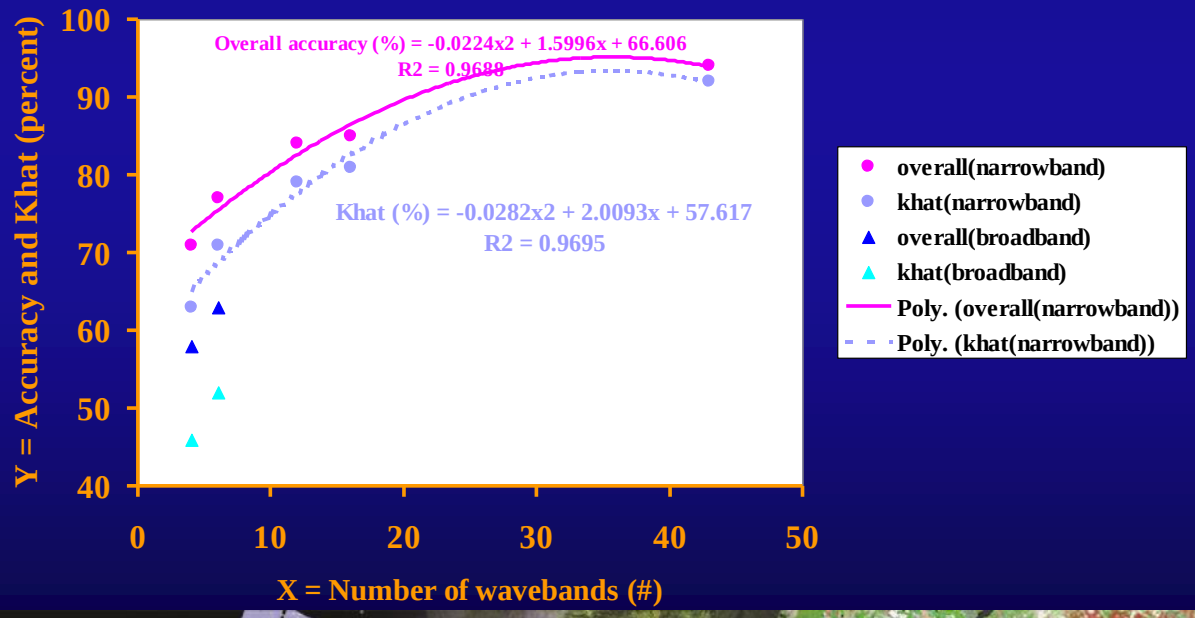
Note: see chapter 17

Crop Type and Crop Characteristics Classifications through

Discriminant Model Error Matrices for Accuracies

5. Improved accuracies in crop or vegetation type or species classification

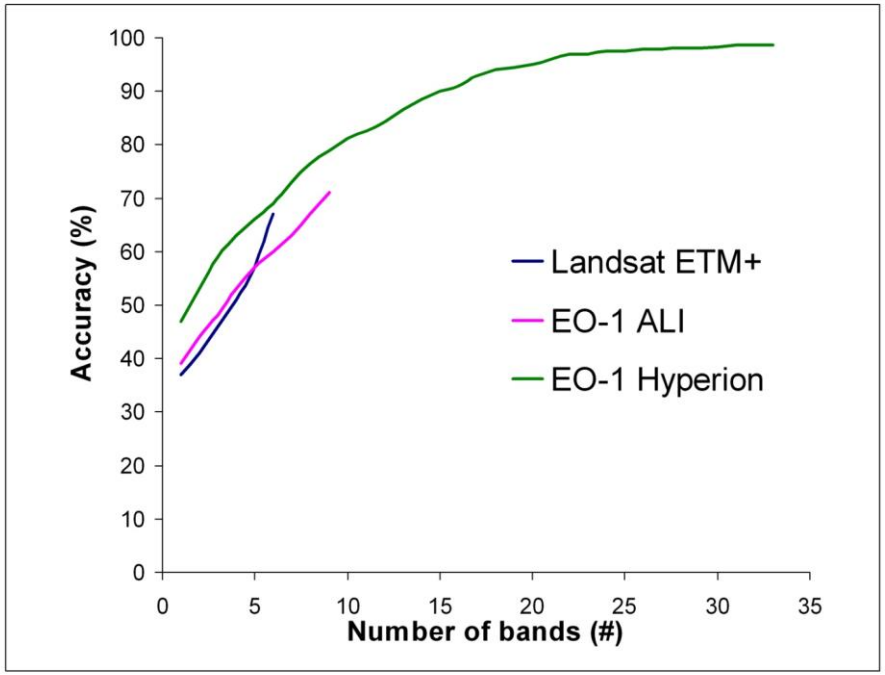
Hyperspectral narrowbands (HNBs) help provide significantly improved accuracies (10%–30%) in classifying vegetation types or species types compared to broadband data.



Crop Type and Crop Characteristics Classifications through

Discriminant Model Error Matrices for Accuracies

Best 4 bands	550, 680, 850, 970
Best 6 bands	550, 680, 850, 970, 1075, 1450
Best 8 bands	550, 680, 850, 970, 1075, 1180, 1450, 2205
Best 10 bands	550, 680, 720, 850, 970, 1075, 1180, 1245, 1450, 2205
Best 12 bands	550, 680, 720, 850, 910, 970, 1075, 1180, 1245, 1450, 1650, 2205
Best 16 bands	490, 515, 550, 570, 680, 720, 850, 900, 970, 1075, 1180, 1245, 1450, 1650, 1950, 2205
Best 20 bands	490, 515, 531, 550, 570, 680, 720, 850, 900, 970, 1075, 1180, 1245, 1450, 1650, 1725, 1950, 2205, 2262, 2359



6. Whole Spectral Analysis (e.g., continuous and entire spectra over 400–2500 nm) using such methods as partial least squares regression (PLSR), wavelet analysis, continuum removal, and spectral angle mapper (SAM) is very useful in many instances even if data volumes are very high.

Knowledge Gain and Knowledge Gaps: Hyperspectral Remote Sensing of C
Whole Spectral Analysis Versus Selective Optir

Note:

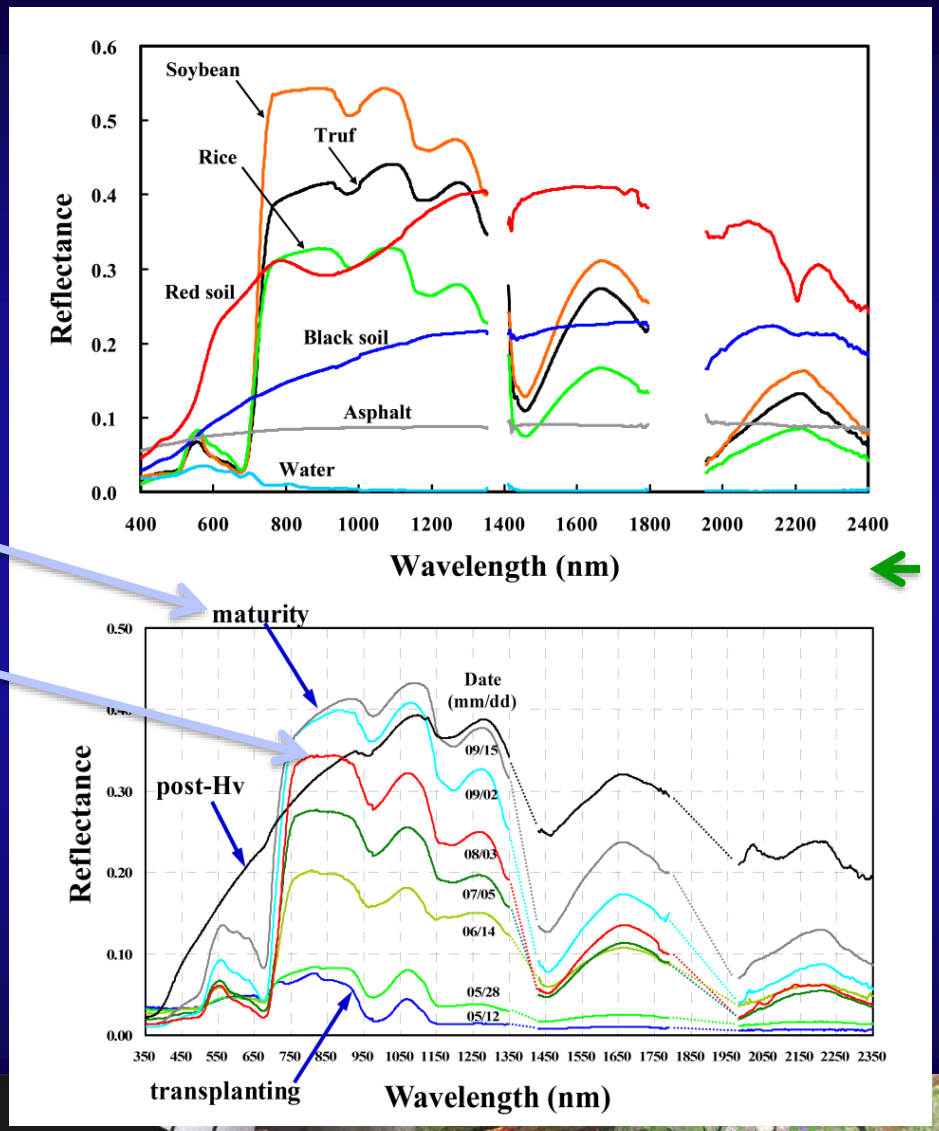
1. Studying the structure of plant canopy (e.g., erectophile vs. planophile) through slope of the spectra in the NIR shoulder (760–900 nm);
2. blueshift in the red-edge (700–740 nm) portion of the spectrum indicates stress due to many causes such as drought and heavy metals and a redshift (shift of the red-edge position toward longer wavelengths) indicates chlorophyll accumulation.

Hyperspectral Remote Sensing of Crops and Vegetation: Knowledge Gained Over Last 50-Years

Whole Spectral Analysis Versus Selective Optimal Bands through

partial least squares regression (PLSR), wavelet analysis, continuum removal, and spectral angle mapper (SAM)

NIR shoulder (760 nm to 900 nm) for mature\senescing rice versus Rice in Vegetative phases



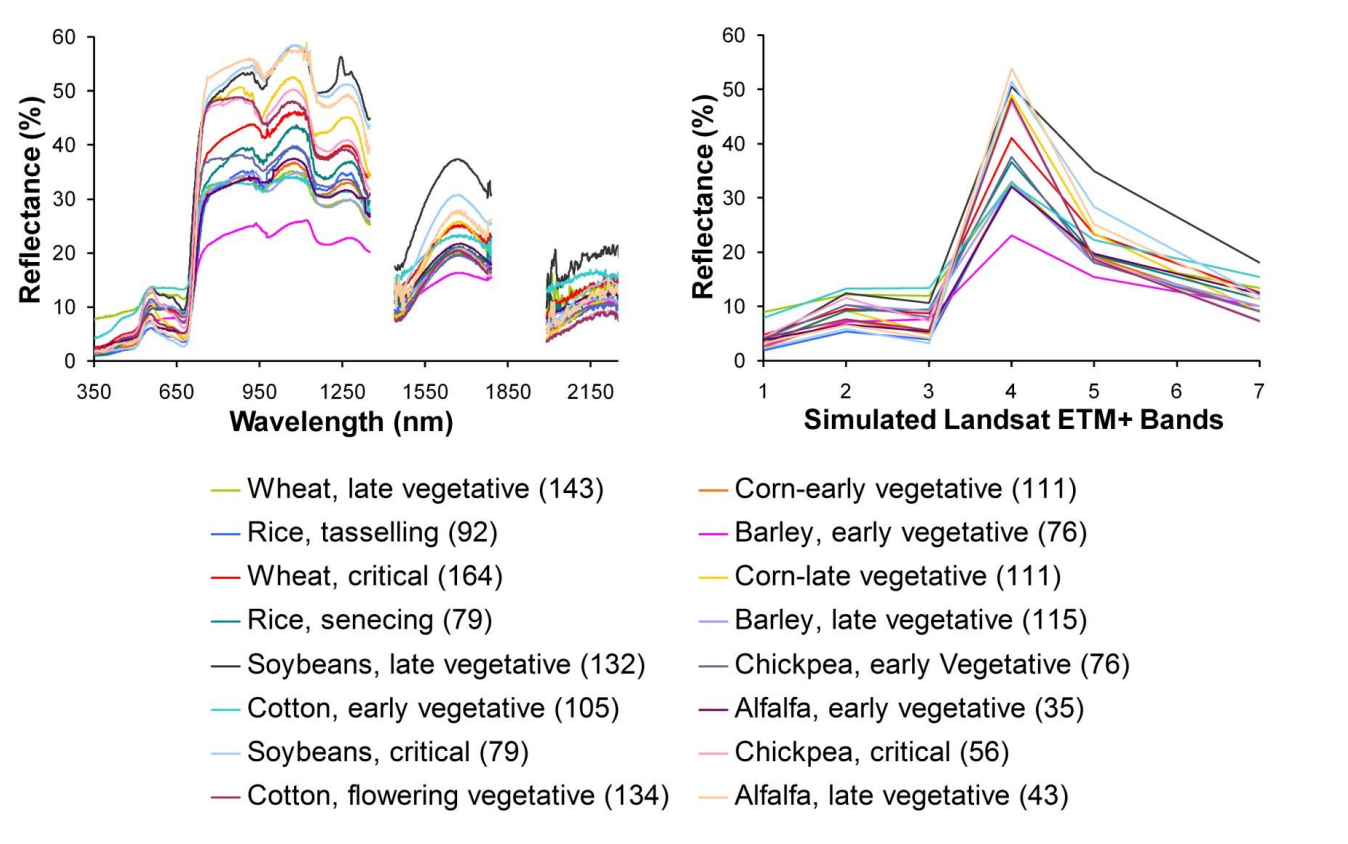
Typical reflectance spectra in agro-ecosystem surfaces (upper), and <u>seasonal changes</u> of spectra in a paddy rice field (lower).

See chapter 3

7. Data continuity for the Past Sensors (e.g., Landsat, SPOT, IRS, IKONOS) through

Synthesis of Hyperspectral Narrowband data

Using hyperspectral narrowband data one can produce any broadband data (e.g., Landsat, Resourcesat, SPOT). Thereby, hyperspectral sensors not only help advance remote sensing science through imaging spectroscopy, but also facilitate data continuity of broadband sensors such as Landsat, SPOT, and IRS.

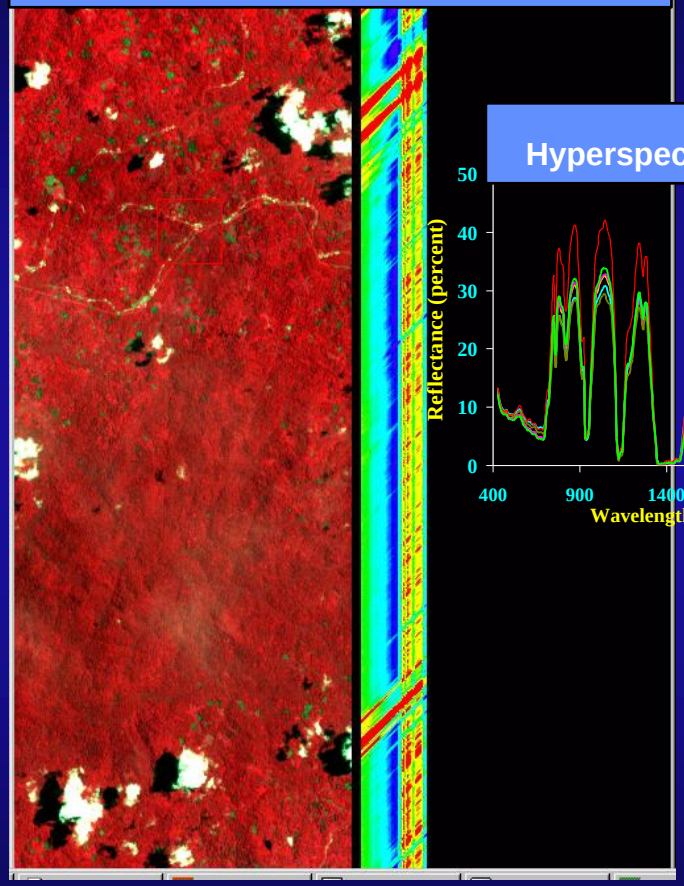


Hyperspectral Remote Sensing of Crops and Vegetation: Knowledge Gained Over Last 50-Years

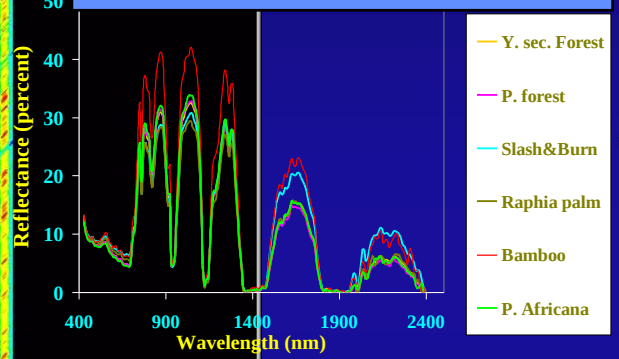
7. Data continuity for the Past Sensors (e.g., Landsat, SPOT, IRS, IKONOS) through

Synthesis of Hyperspectral Narrowband data

Hyperspectral image data cube

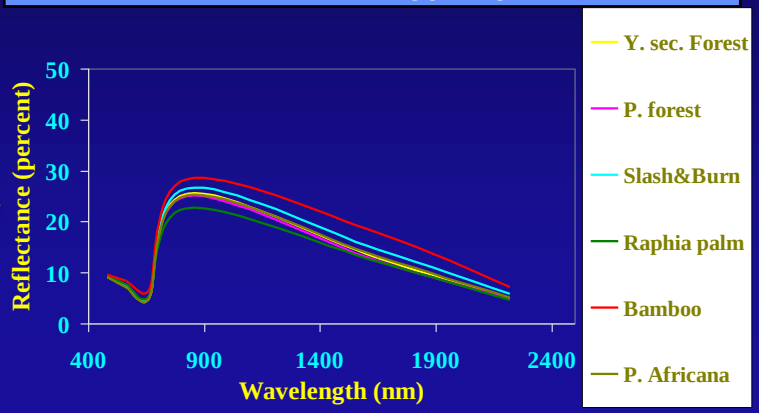


Hyperspectral image spectra

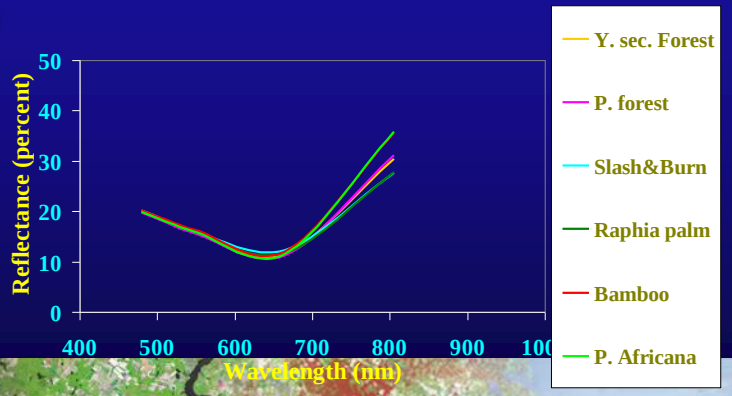


Generating Broadbands (e.g., Landsat, IKONOS) from Narrowbands (e.g., HyspIRI)

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



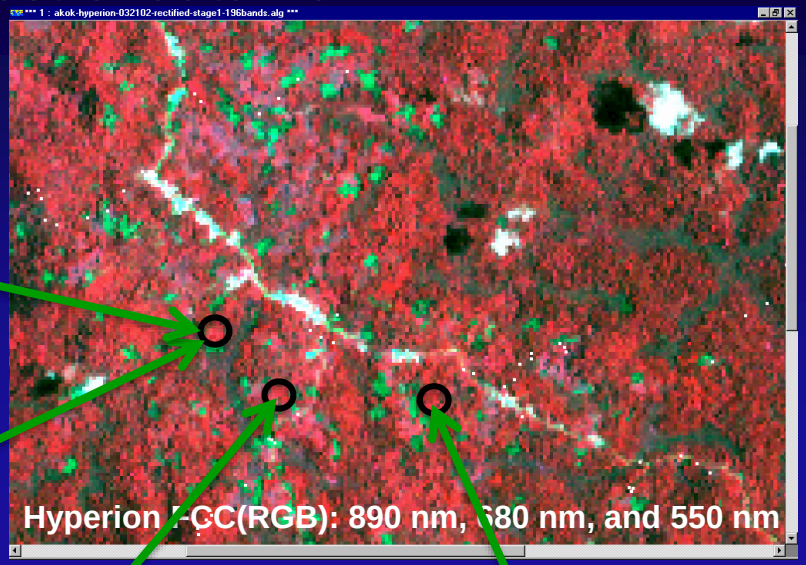
Imaging spectroscopy: 242 hyperspectral bands, each of 5 or 10 nm wide, in 400-2500 nm spectral range.

USGS science for a changing world

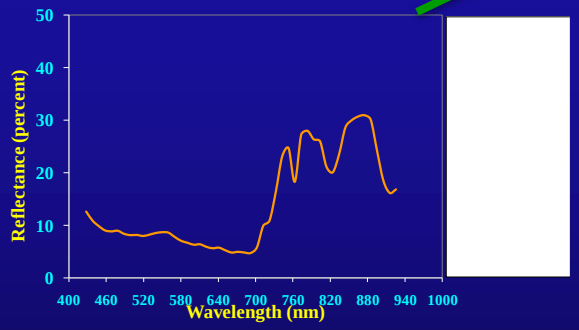
U.S. Geological Survey
U.S. Department of Interior

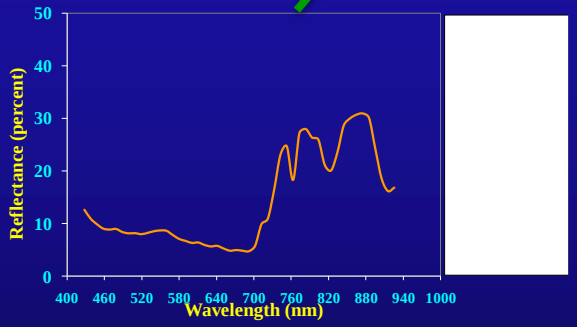
Hyperspectral Remote Sensing of Crops and Vegetation: Knowledge Gained Over Last 50-Years

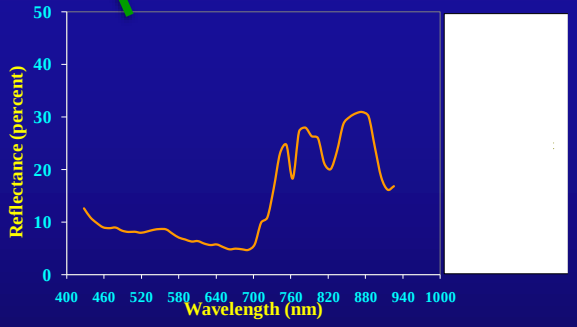
8. Spectral Signature of Vegetation Species (e.g., P. Africana) from Available Spectral data Bank



Hyperion FCC(RGB): 890 nm, 680 nm, and 550 nm



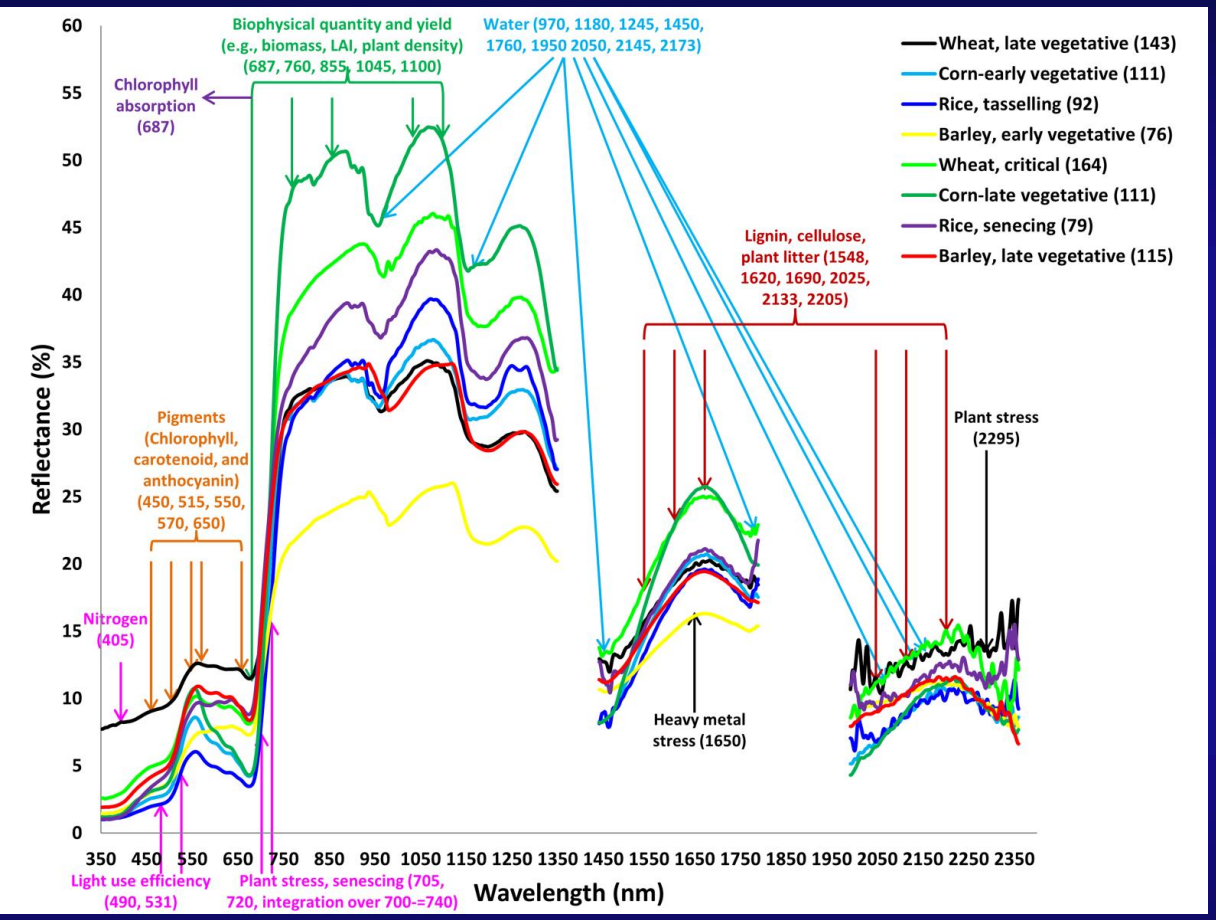




There are numerous uses of spectral data bank

Hyperspectral Remote Sensing of Crops and Vegetation: Knowledge Gained Over Last 50-Years

9. Identifying Hyperspectral Narrowband (HNB's) for Specific Applications through Comprehensive Research



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.

Beyond Hyperspectral Data: Hyperspectral+LiDAR+Thermal

Strengths of hyperspectral data in biophysical and biochemical characterization of vegetation are well known.

LiDAR

However, better characterization and modeling of the vegetation height/depth, crown sizes, basal area, biomass, and structure will require LIDAR.

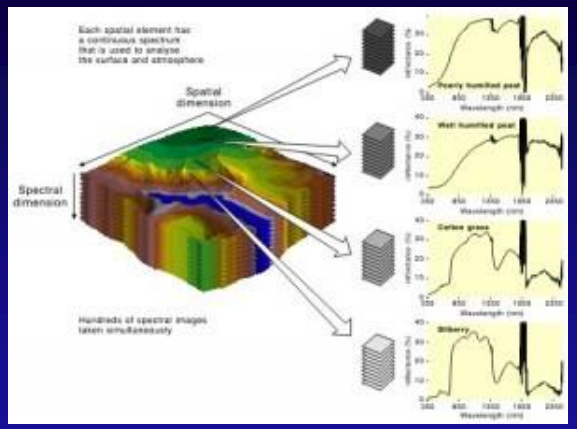
Thermal

Further plant water properties are better understood using thermal data.

Hyperspectral+LiDAR+Thermal

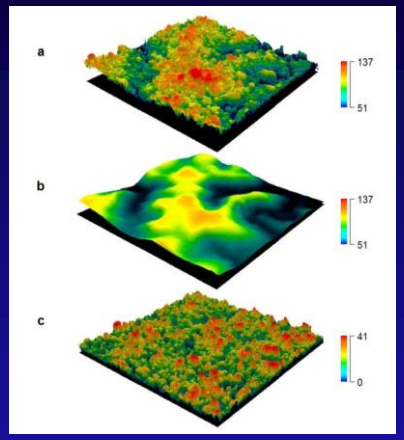
Given these facts, simultaneous acquisition and integration of hyperspectral data along with LIDAR and thermal data are considered the future of remote sensing.

Beyond Hyperspectral Data: Hyperspectral+LiDAR+Thermal



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
height
canopy cover
leaf area
canopy chlorophyll content, and
canopy water content

Note: see chapter 20, Thomas et al.

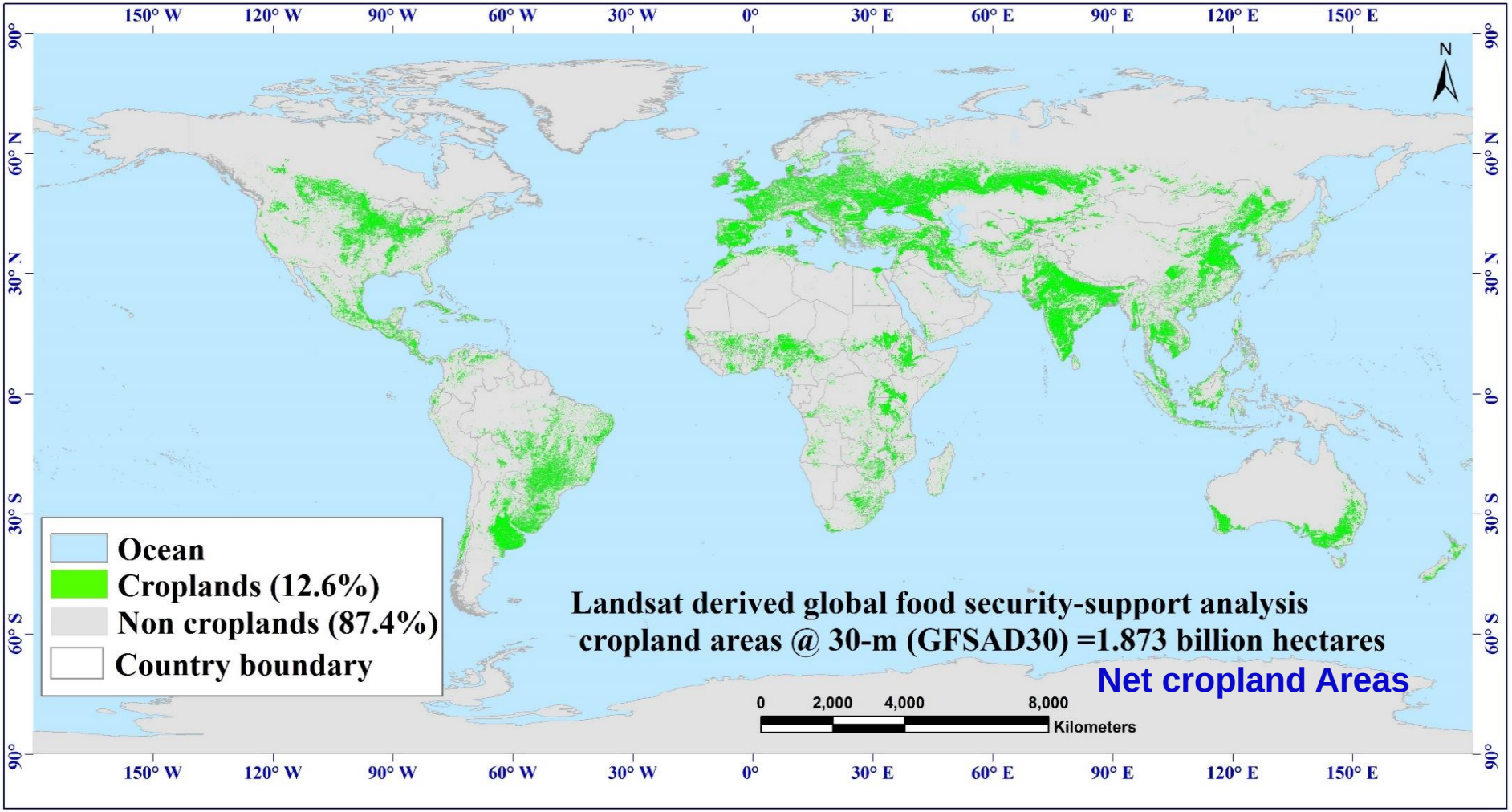
Global Croplands @ 30-m

Results: Cropland Extent Distribution

https://web.croplands.org/app/map
croplands.org
https://geography.wr.usgs.gov/science/croplands/index.html

Global 30-m Landsat-derived Cropland Extent, Areas, and Accuracies

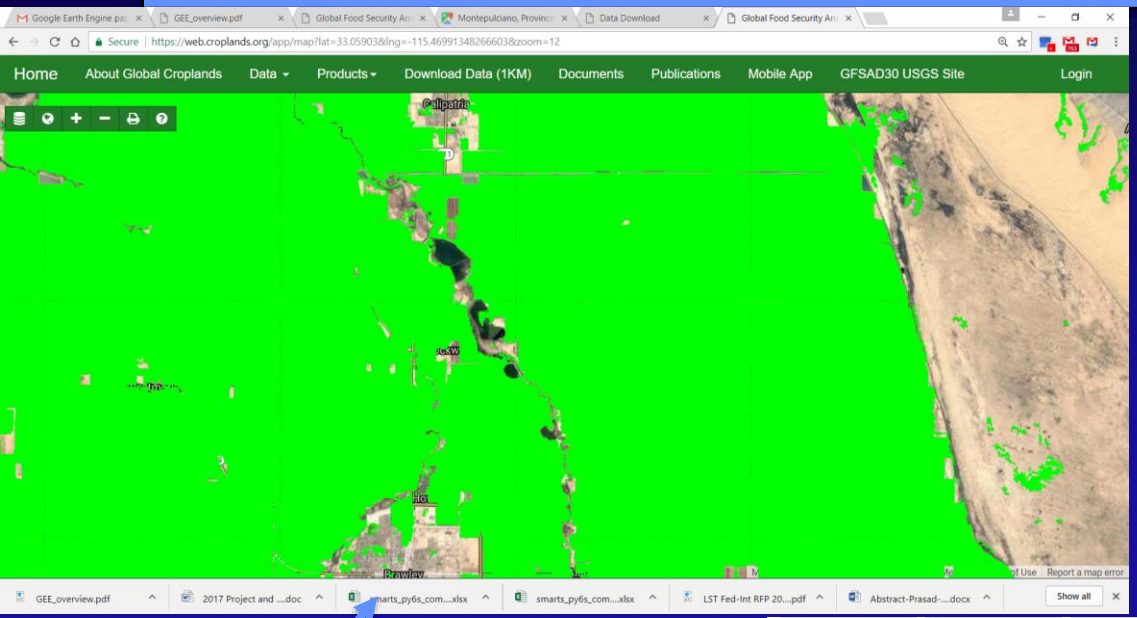
30-m Cropland Extent Product of the World

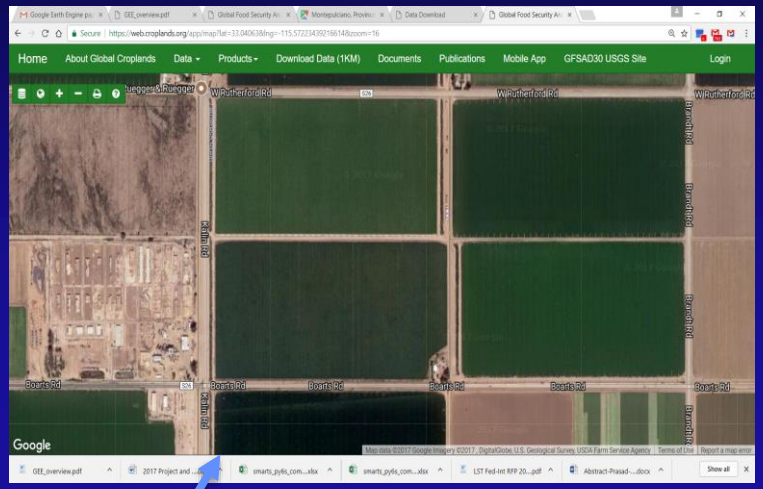


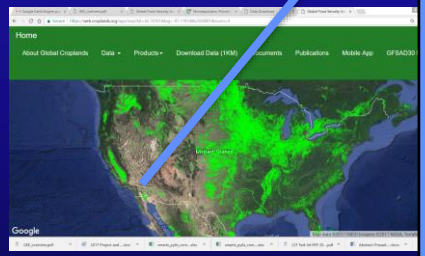
Global 30-m Landsat-derived Cropland Extent, Areas, and Accuracies

Downstream of Salton Sea, Arizona, USA: Agricultural Croplands

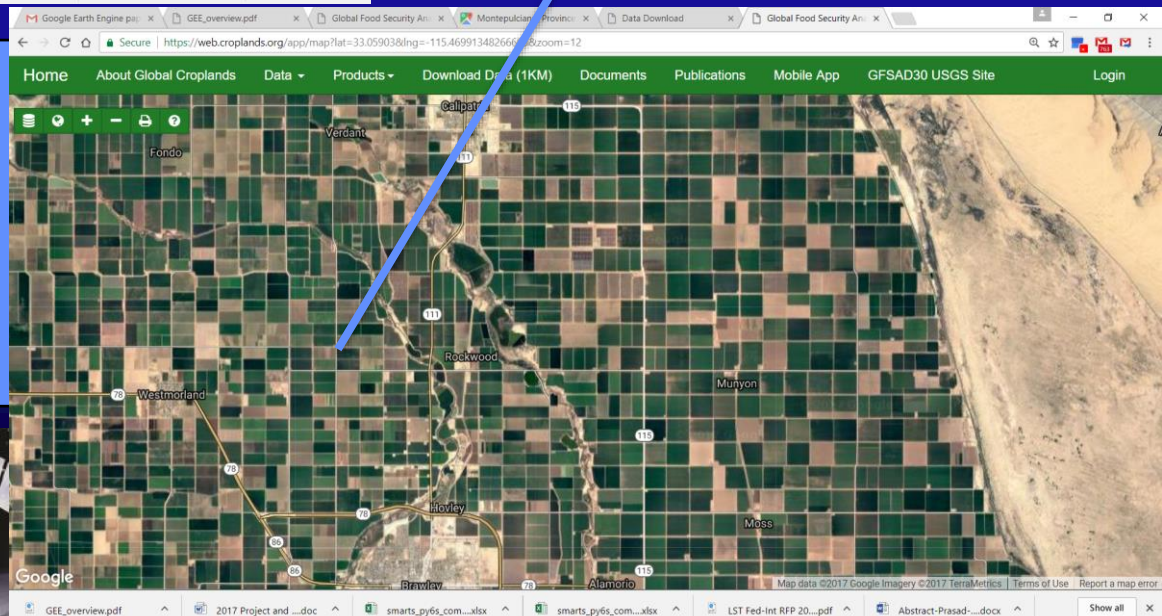
https://croplands.org/app/map; https://croplands.org/







USA ranked # 2 with 167.8 Mha of net cropland areas



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Global Croplands @ 30-m

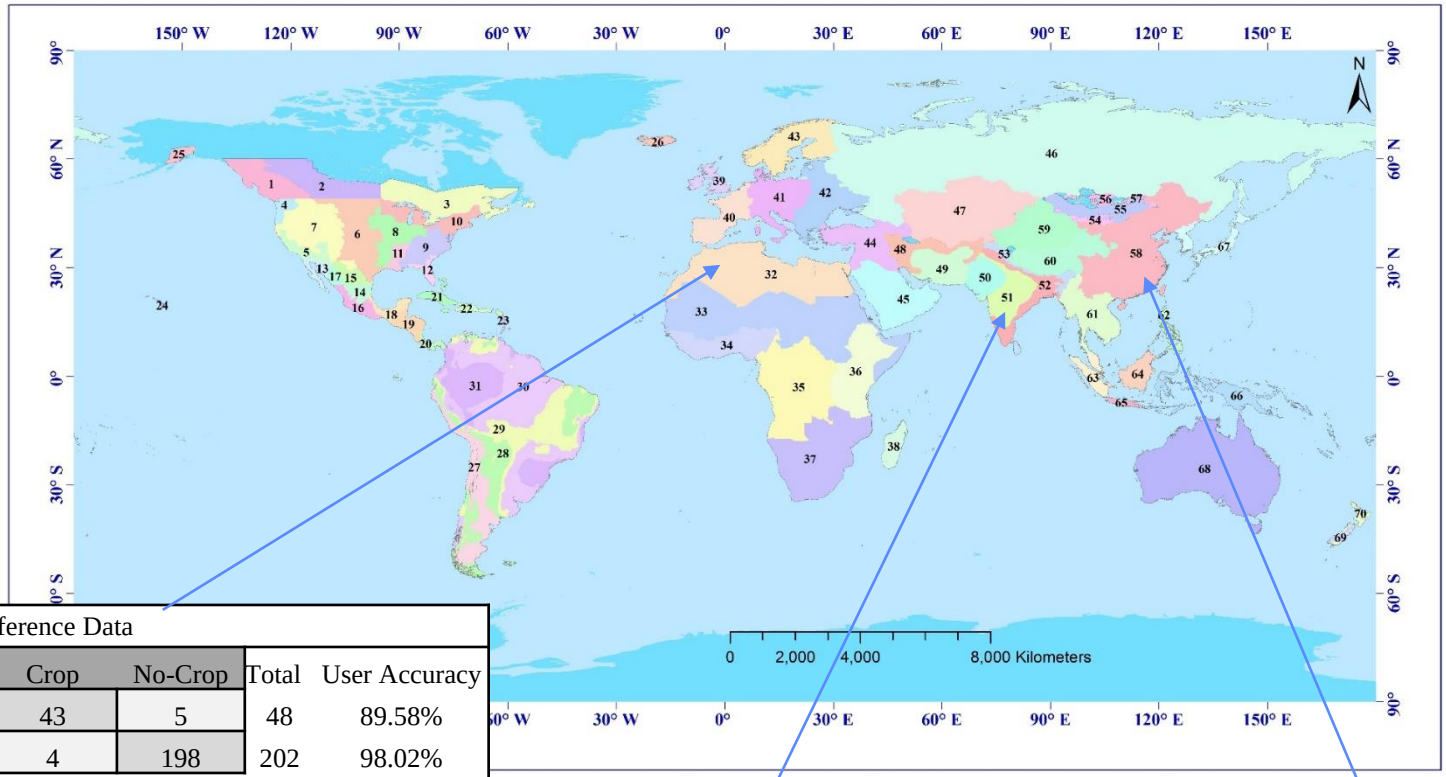
Results:

30-m Global Cropland Accuracies

https://web.croplands.org/app/map
croplands.org
https://geography.wr.usgs.gov/science/croplands/index.html

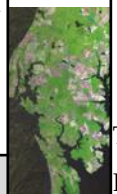
Global 30-m Landsat-derived Cropland Extent, Areas, and Accuracies

Accuracy Error matrices: Zone-by-Zone Error Matrices



		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	43	5	48	89.58%
	No-Crop	4	198	202	98.02%
Total		47	203	250	
Producer Accuracy		91.49%	97.54%		**96.40%**

		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	140	18	158	88.61%
	No-Crop	24	67	91	73.63%
Total		164	85	249	
Producer Accuracy		85.37%	78.82%		**83.13%**



		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	255	48	303	84.16%
	No-Crop	51	830	881	94.21%
Total		306	878	1,184	
Producer Accuracy		83.33%	94.53%		**91.64%**

Global Croplands @ 30-m

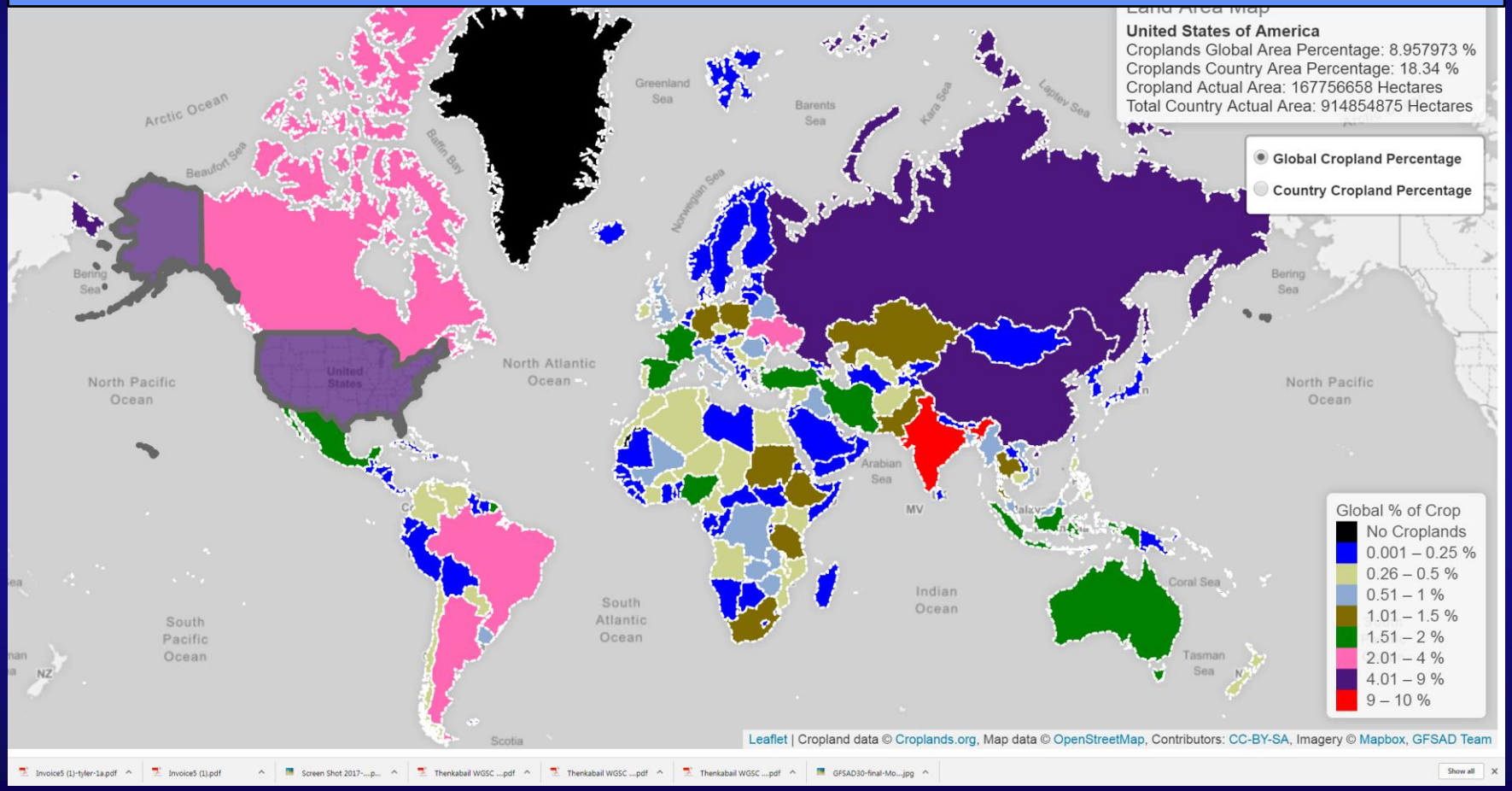
Results: Cropland Areas by Country

https://web.croplands.org/app/map
croplands.org
https://geography.wr.usgs.gov/science/croplands/index.html

Global 30-m Landsat-derived Cropland Extent, Areas, and Accuracies

30-m Net Cropland Area as % of Global Net Cropland Area

Interactive area Map @:
https://web.croplands.org/app/map/statsMap



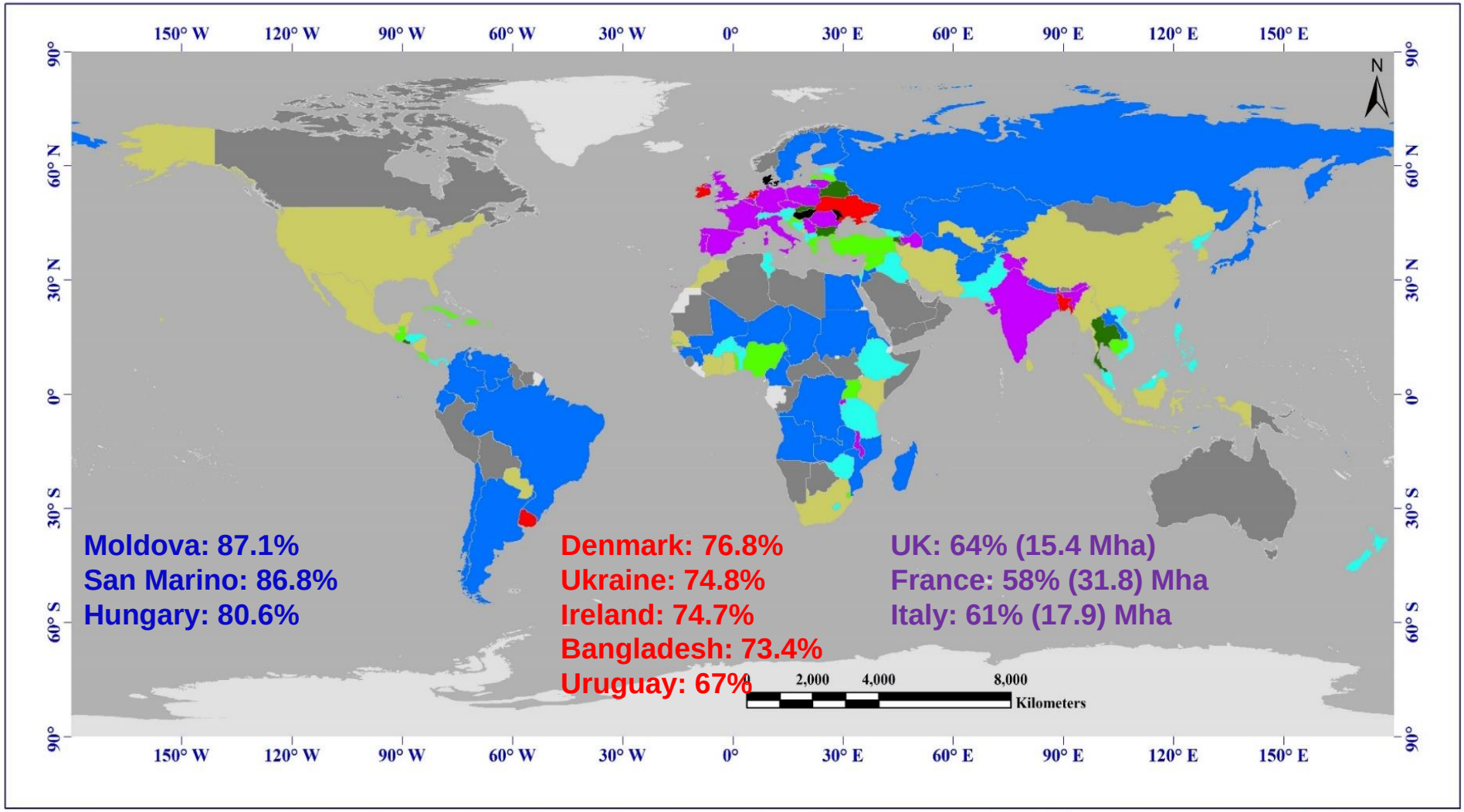
Global Croplands @ 30-m

Results: Cropland Areas as % of Country Geographic Areas

https://web.croplands.org/app/map
croplands.org
https://geography.wr.usgs.gov/science/croplands/index.html

Global 30-m Landsat-derived Cropland Extent, Areas, and Accuracies

30-m Net Cropland Area as % of Geographic Area of the Country



Cropland Areas as % of County Geographic Area

- 0.0 - 0.1
- 0.2 - 5.0
- 5.1 - 15.0
- 15.1 - 25.0
- 25.1 - 35.0
- 35.1 - 45.0
- 45.1 - 55.0
- 55.1 - 65.0
- 65.1 - 75.0
- 75.1 - 87.1

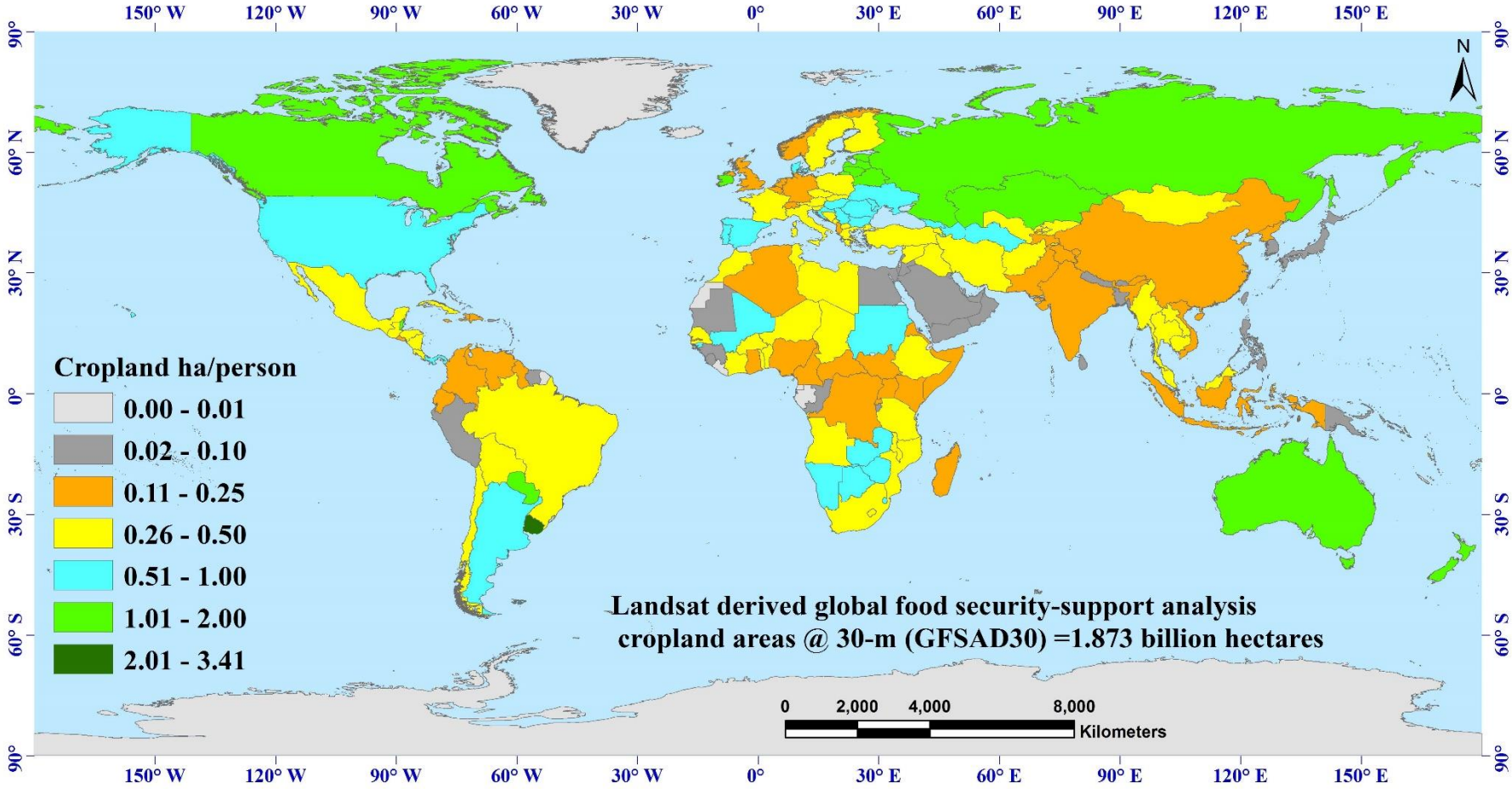
Global Croplands @ 30-m

Results: Cropland Areas\person\country

https://web.croplands.org/app/map
croplands.org
https://geography.wr.usgs.gov/science/croplands/index.html

Global 30-m Landsat-derived Cropland Extent, Areas, and Accuracies

30-m Cropland Area as ha\per person per Country



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Hyperspectral Remote Sensing of Vegetation

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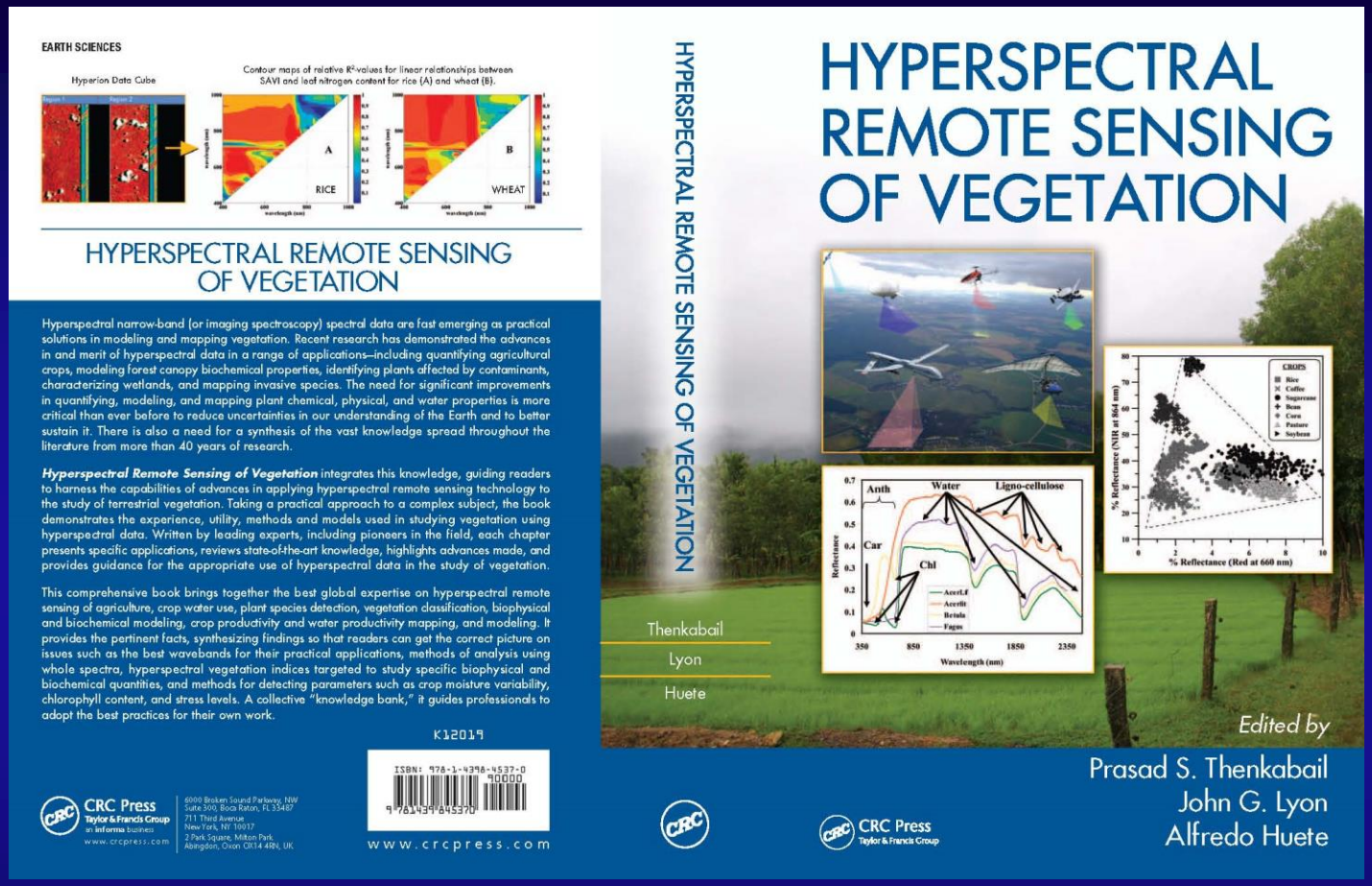

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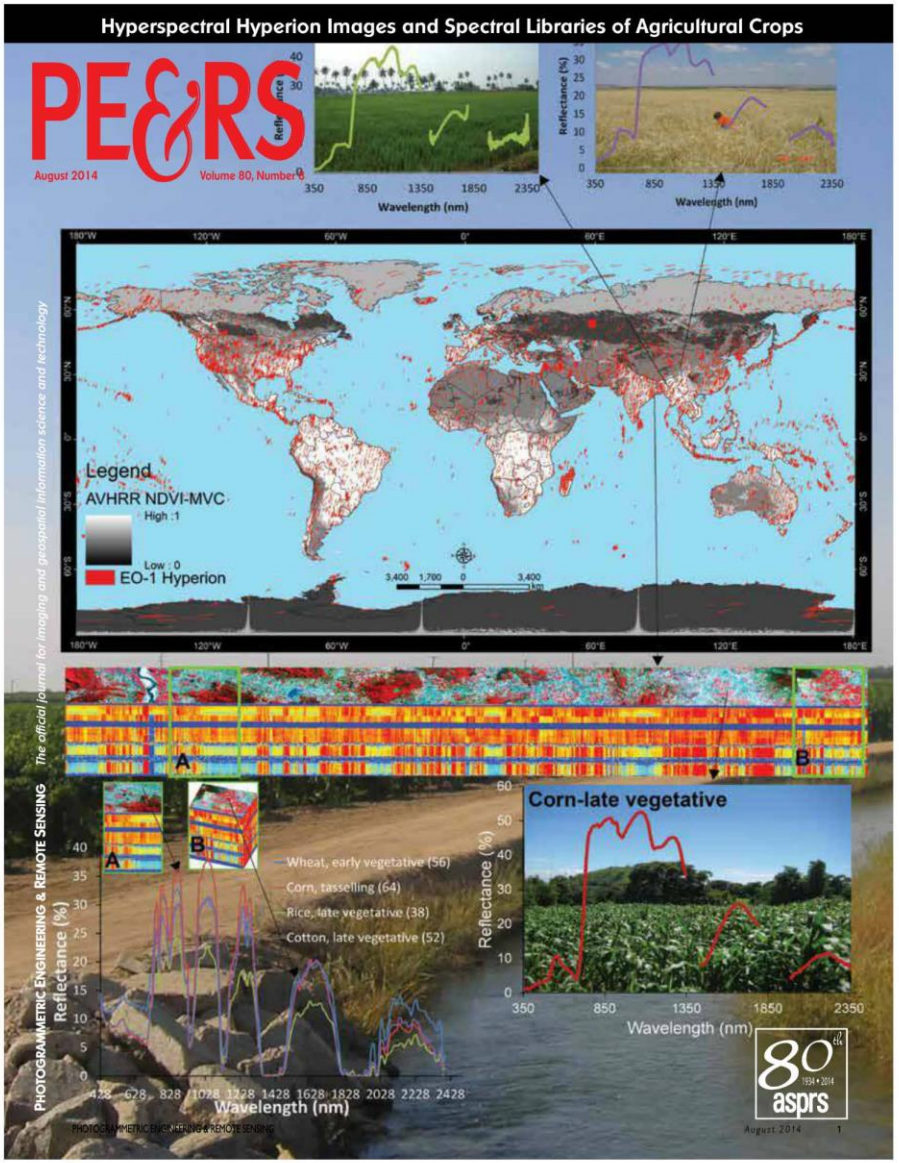

U.S. Geological Survey
U.S. Department of Interior

Recent Publications

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.

IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 6, NO. 2, APRIL 2013 1

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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Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JSTARS.2013.2252601

Hyperspectral Remote Sensing (Imaging Spectroscopy) for Vegetation Studies

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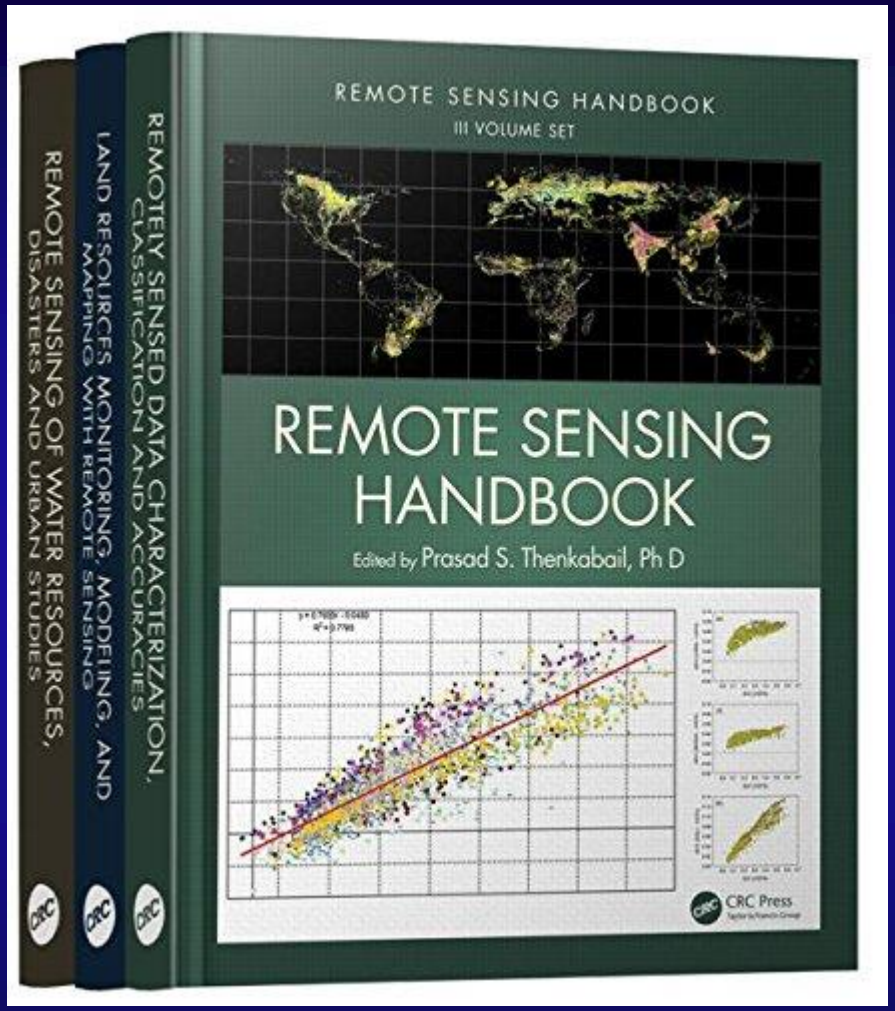

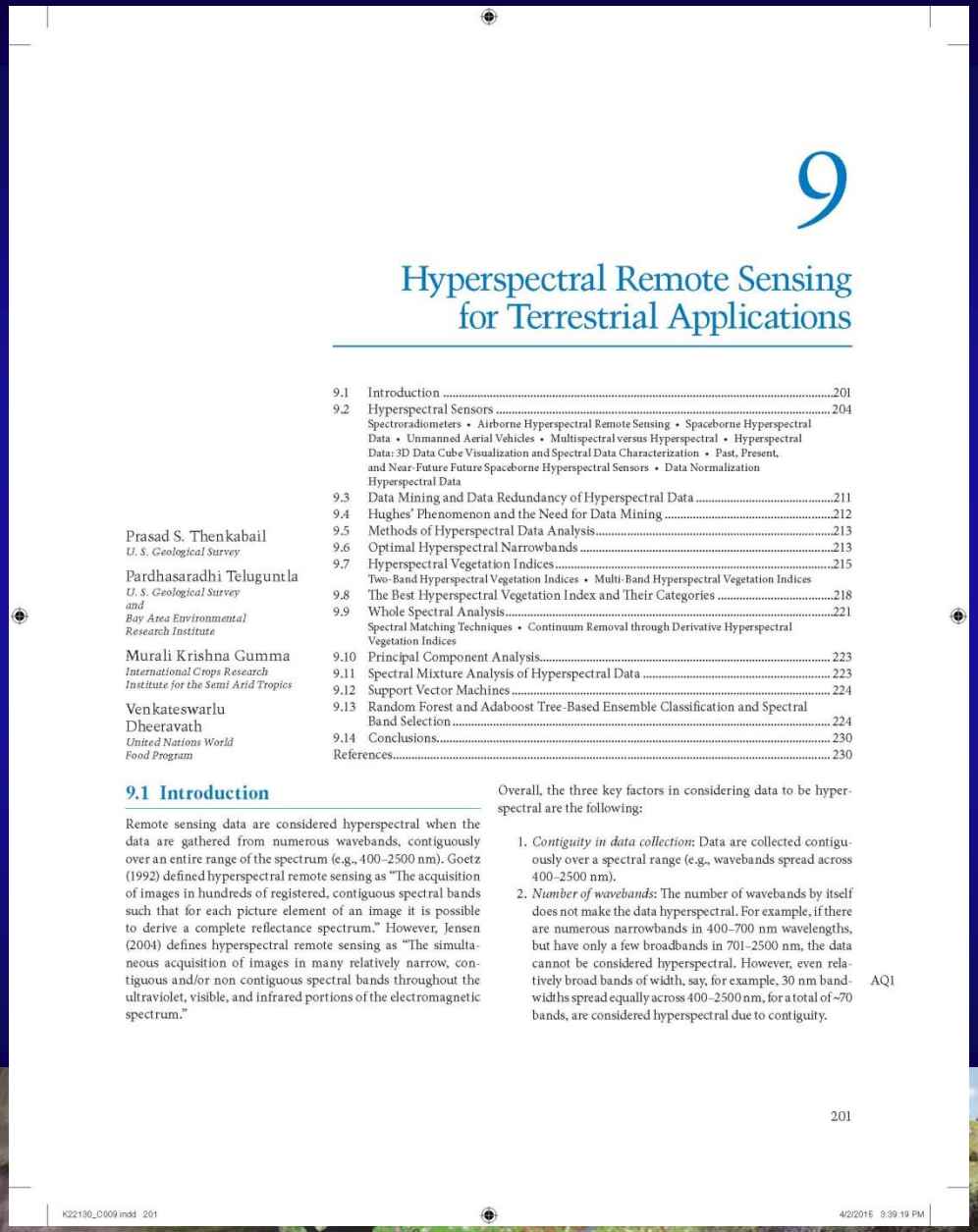

9

Hyperspectral Remote Sensing for Terrestrial Applications

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9.1 Introduction

Remote sensing data are considered hyperspectral when the data are gathered from numerous wavebands, contiguously over an entire range of the spectrum (e.g., 400–2500 nm). Goetz (1992) defined hyperspectral remote sensing as "The acquisition of images in hundreds of registered, contiguous spectral bands such that for each picture element of an image it is possible to derive a complete reflectance spectrum." However, Jensen (2004) defines hyperspectral remote sensing as "The simultaneous acquisition of images in many relatively narrow, contiguous and/or non contiguous spectral bands throughout the ultraviolet, visible, and infrared portions of the electromagnetic spectrum."

Overall, the three key factors in considering data to be hyperspectral are the following:

1. *Contiguity in data collection*: Data are collected contiguously over a spectral range (e.g., wavebands spread across 400–2500 nm).
2. *Number of wavebands*: The number of wavebands by itself does not make the data hyperspectral. For example, if there are numerous narrowbands in 400–700 nm wavelengths, but have only a few broadbands in 701–2500 nm, the data cannot be considered hyperspectral. However, even relatively broad bands of width, say, for example, 30 nm bandwidths spread equally across 400–2500 nm, for a total of ~70 bands, are considered hyperspectral due to contiguity. AQ1

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