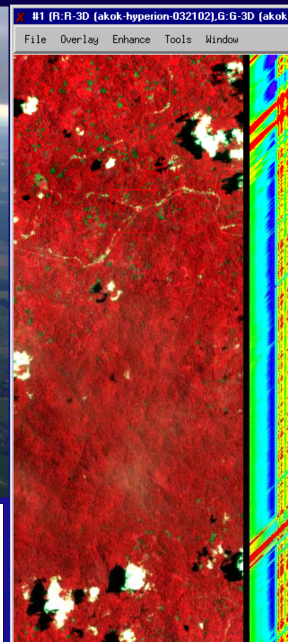
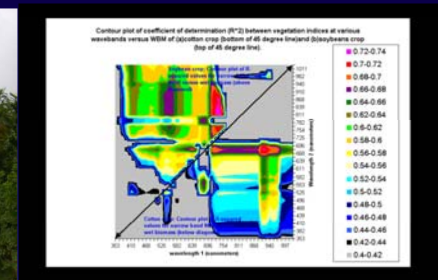
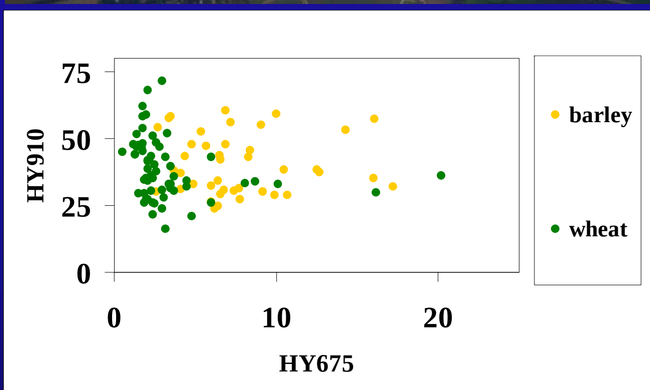
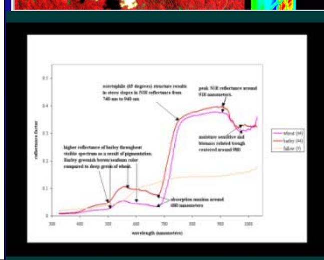
Advanced Hyperspectral Remote sensing of the Terrestrial Environment

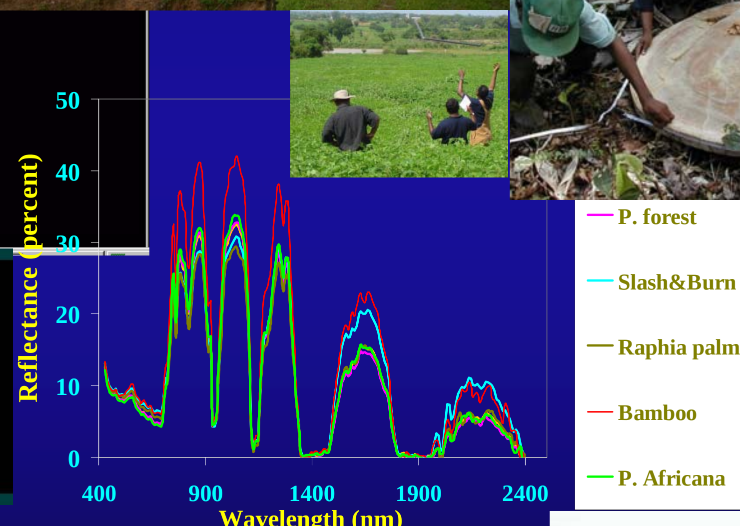
Lecture # 4: Applications, Societal Benefits, Discussions











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

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

USGS
science for a changing world
U.S. Geological Survey
U.S. Department of Interior

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

Hyperspectral Remote Sensing 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;

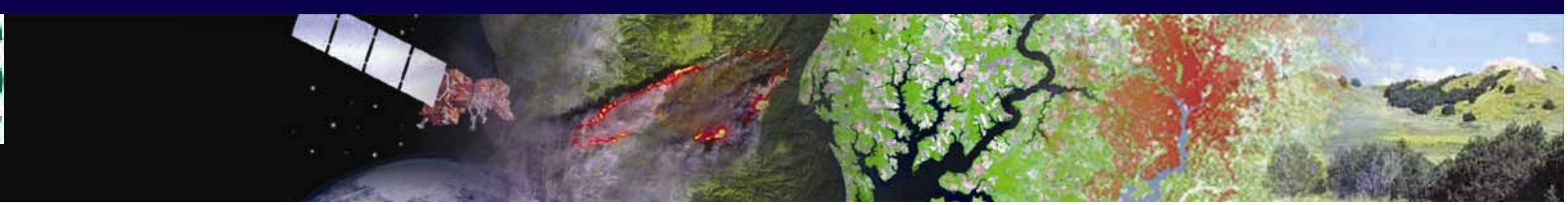
1.2. Explaining greater variability in modeling vegetation and crop biophysical, yield, and biochemical characteristics;

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.

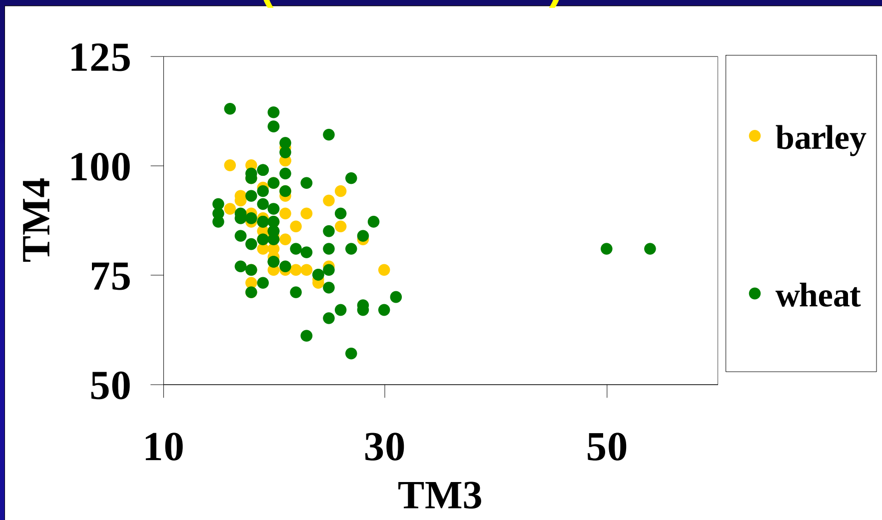


Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

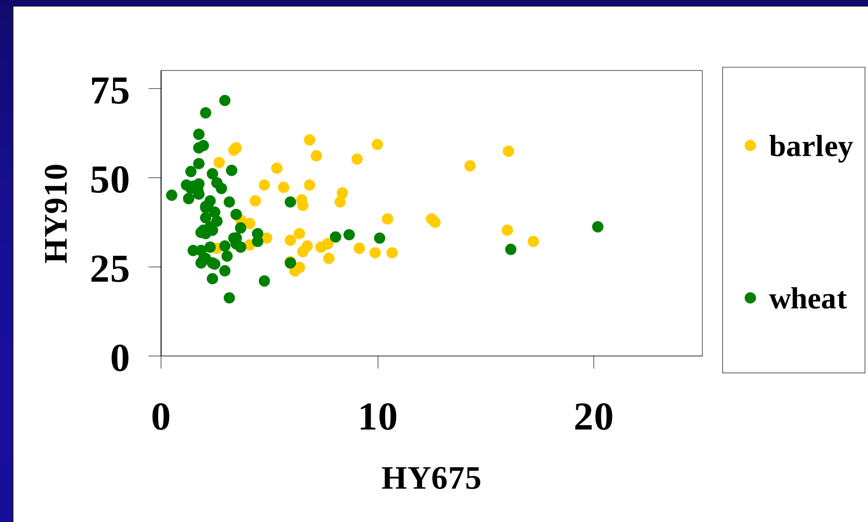
1.1a. Discriminating\Separating Vegetation Types

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

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



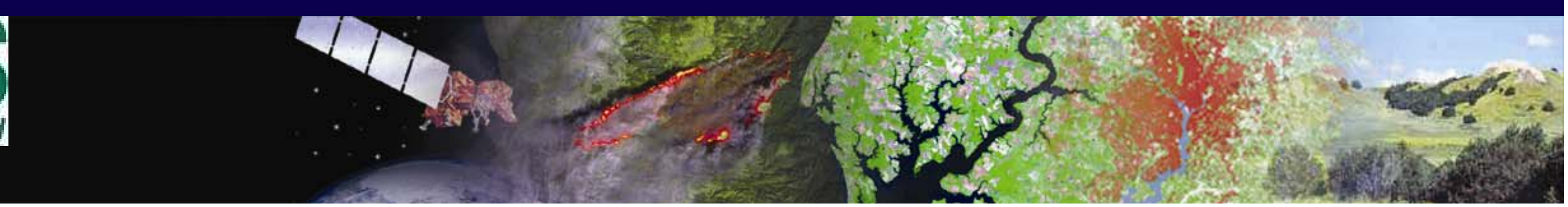
Narrow-band NIR vs. Red




Barley


Wheat

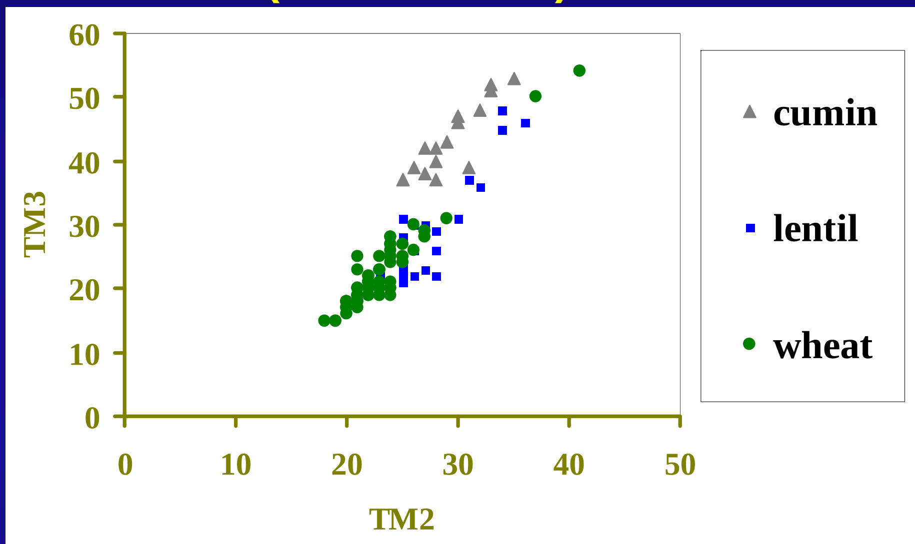
Numerous narrow-bands provide unique opportunity to discriminate different crops and vegetation.



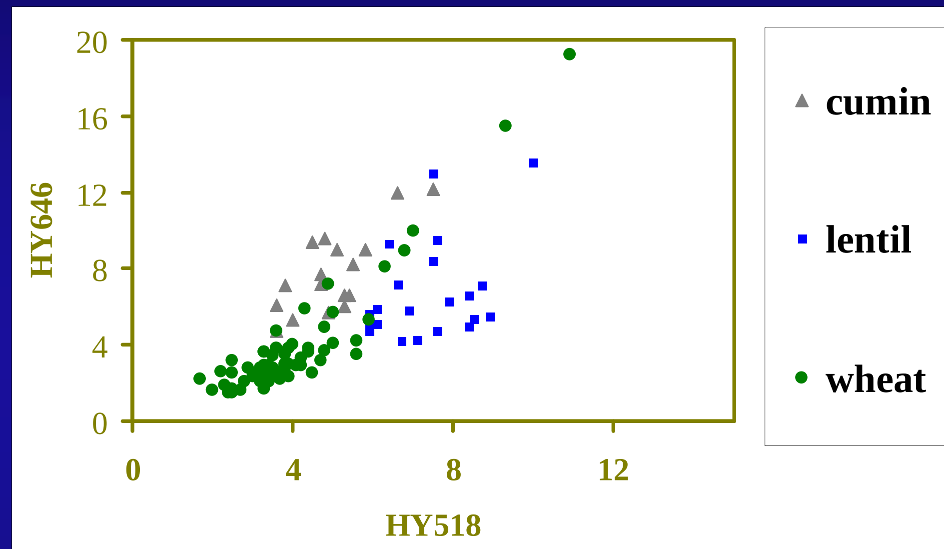
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.1b. Discriminating\Separating Vegetation Types

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



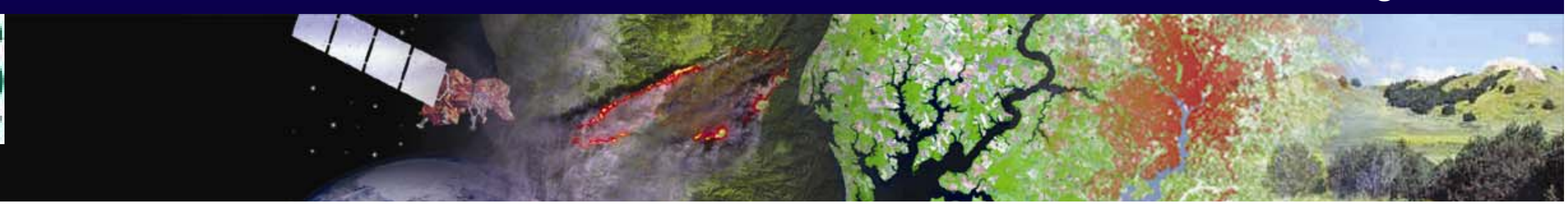
Narrow-band Red vs. Green



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

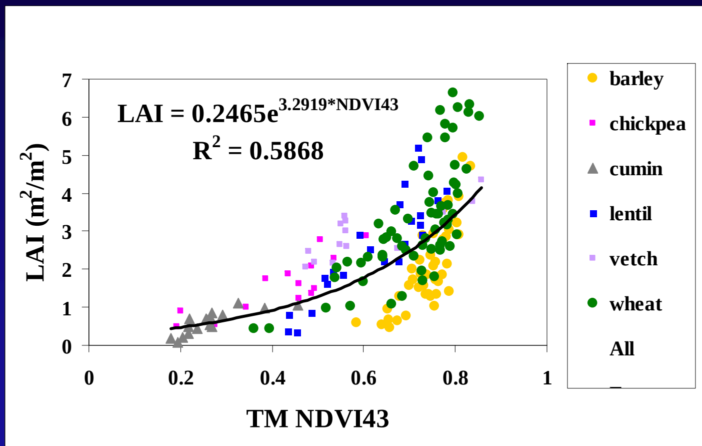
USGS
science for a changing world

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

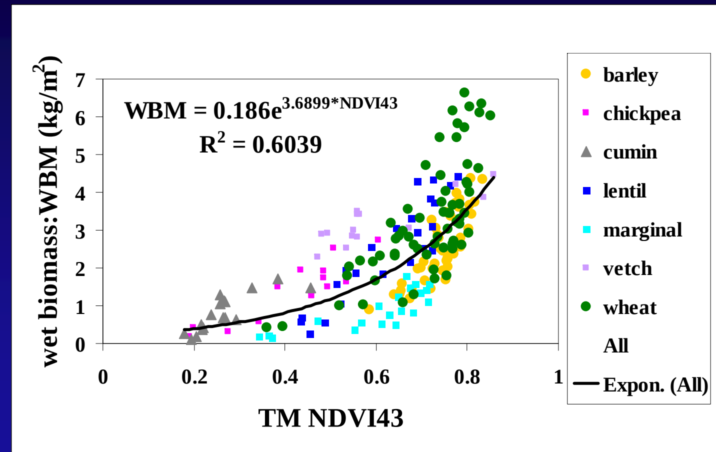


Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

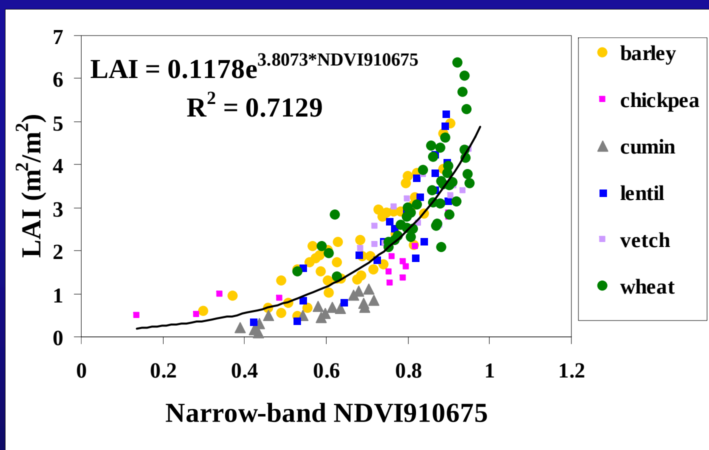
1.2a. Improved biophysical and biochemical models of Vegetation



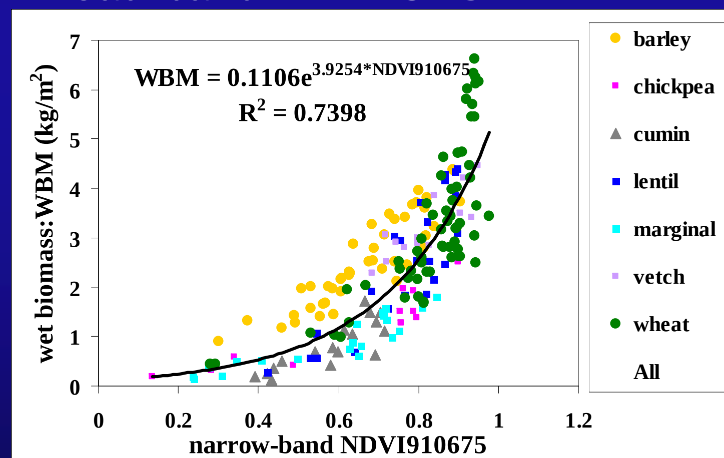
Broad-band NDVI43 vs. LAI



Broad-band NDVI43 vs. WBM



Narrow-band NDVI43 vs. LAI

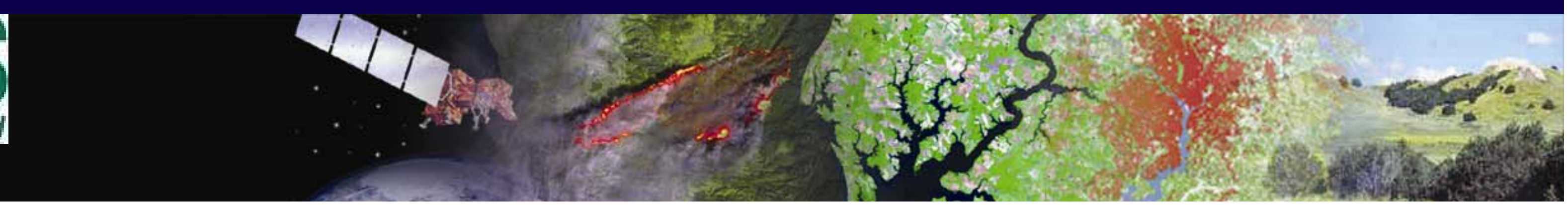


Narrow-band NDVI43 vs. WBM

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.

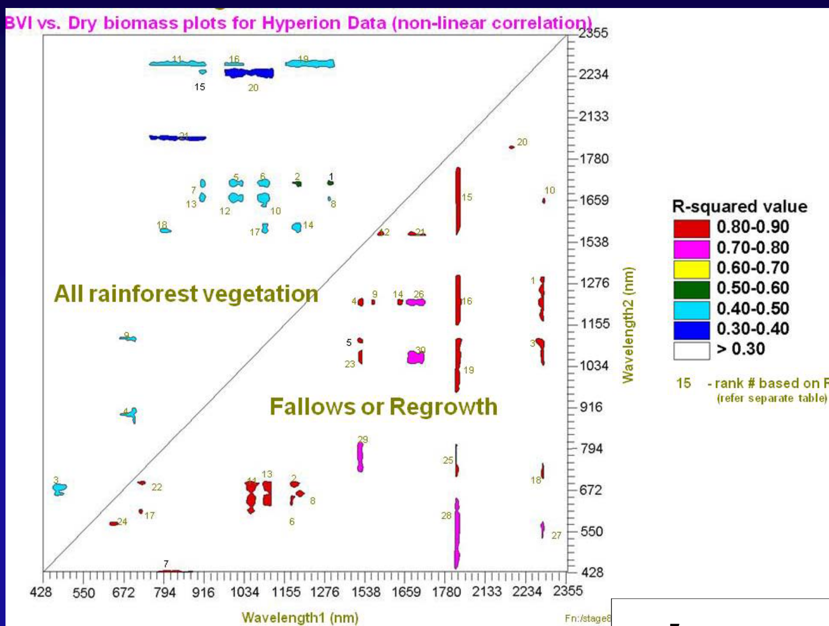
science for a changing world

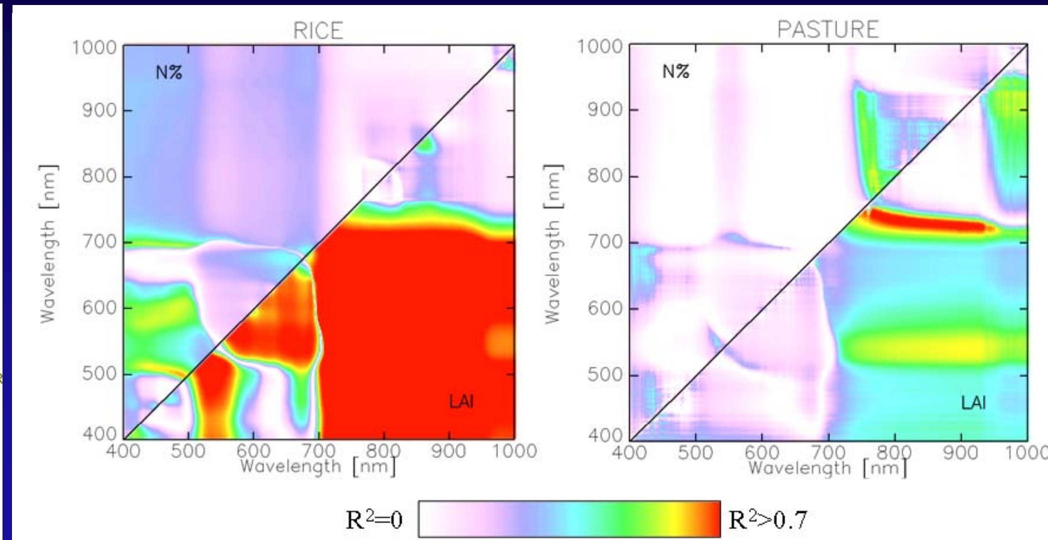


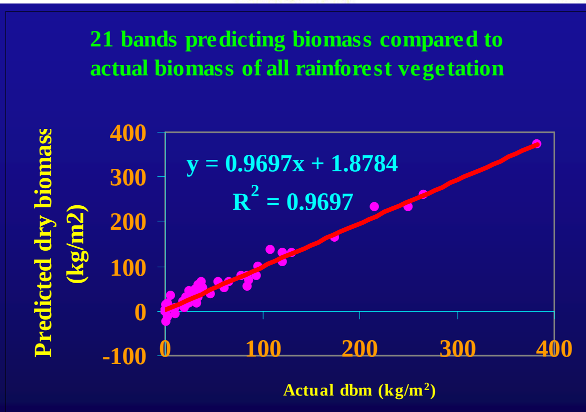
U.S. Geological Survey
U.S. Department of Interior

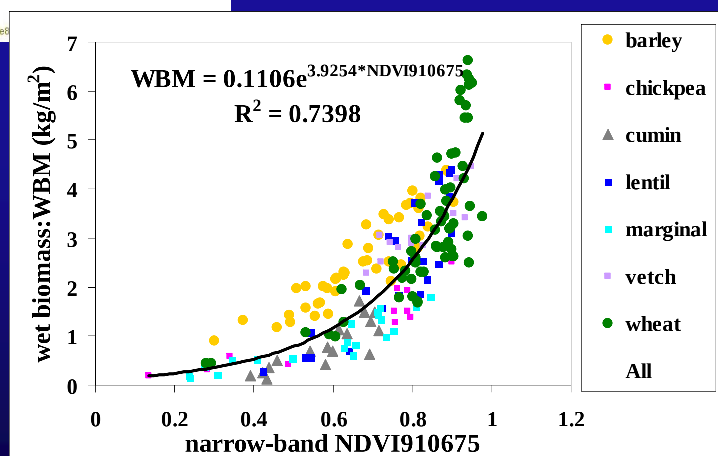
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

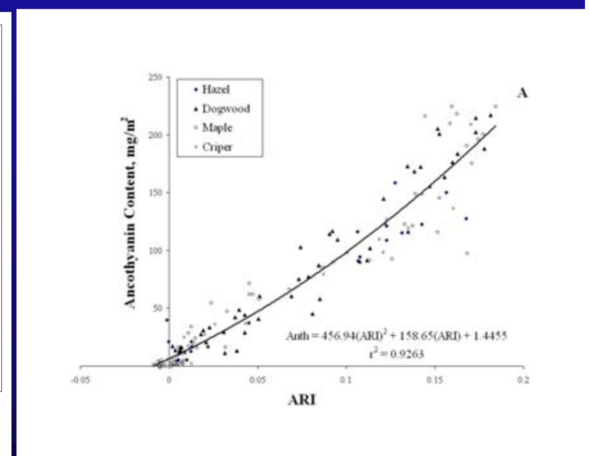
1.2b. Improved biophysical and biochemical models of Vegetation





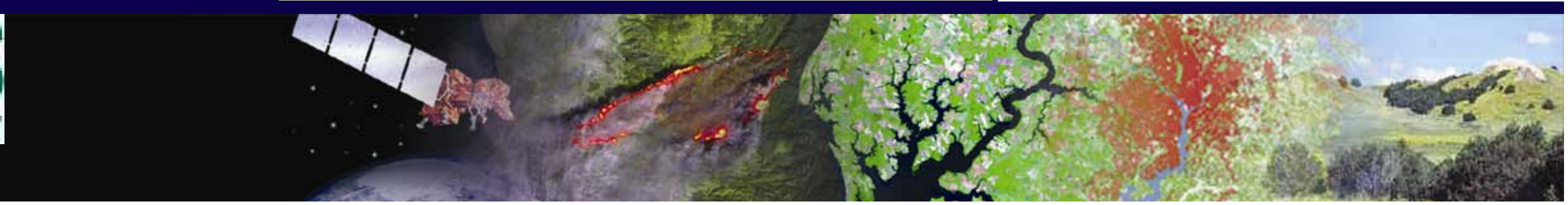






science for a changing world

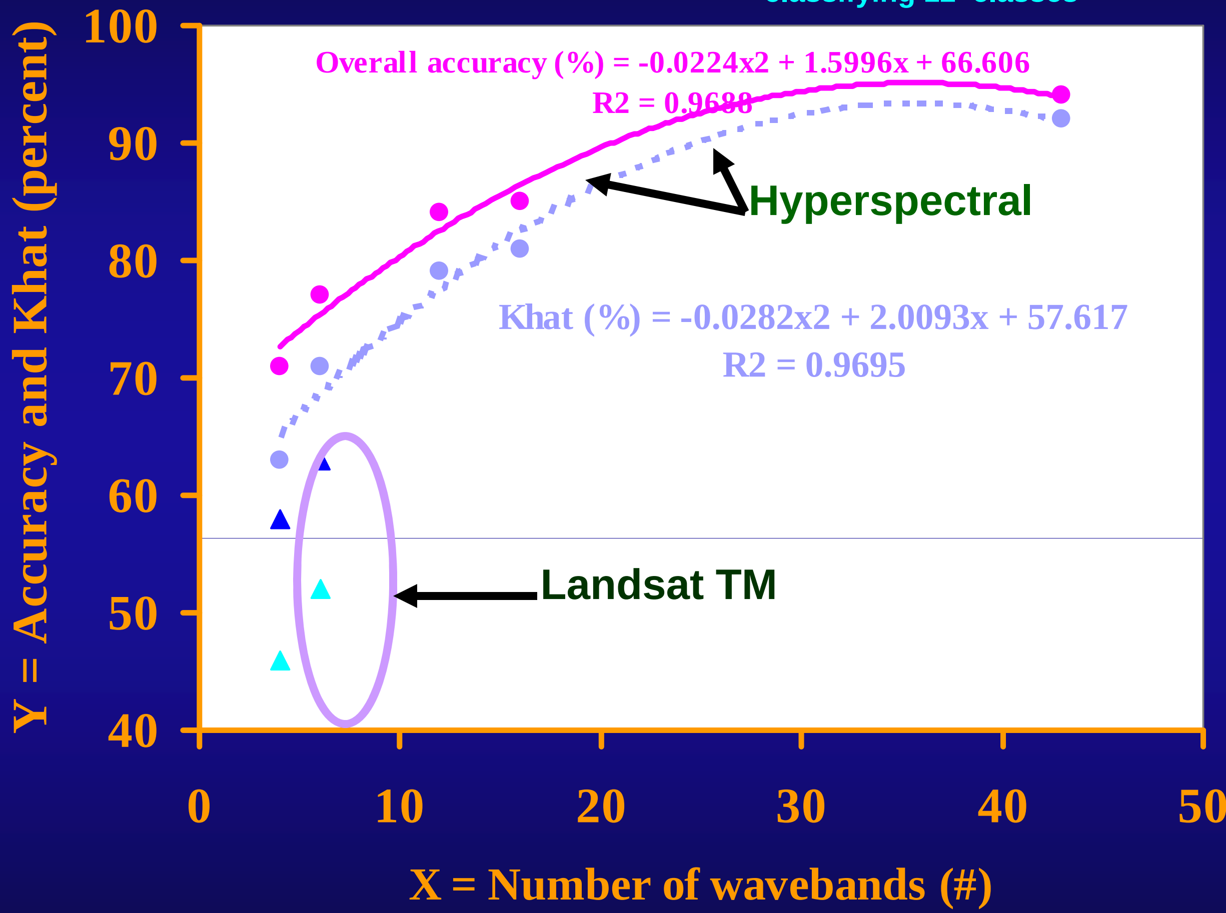
U.S. Geological Survey
U.S. Department of Interior



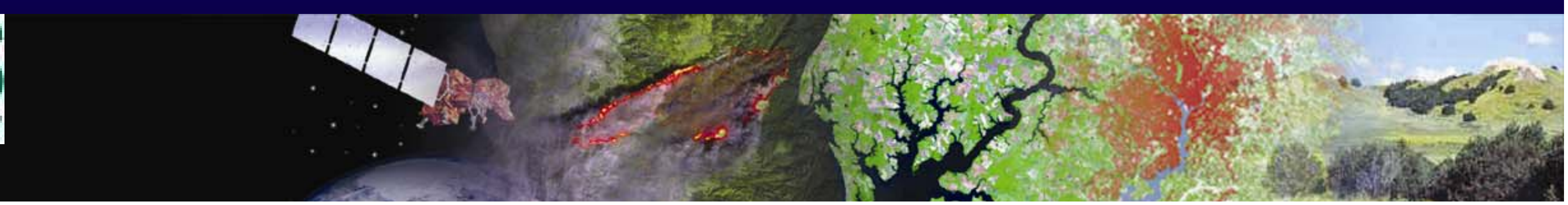
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.3a. 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;**

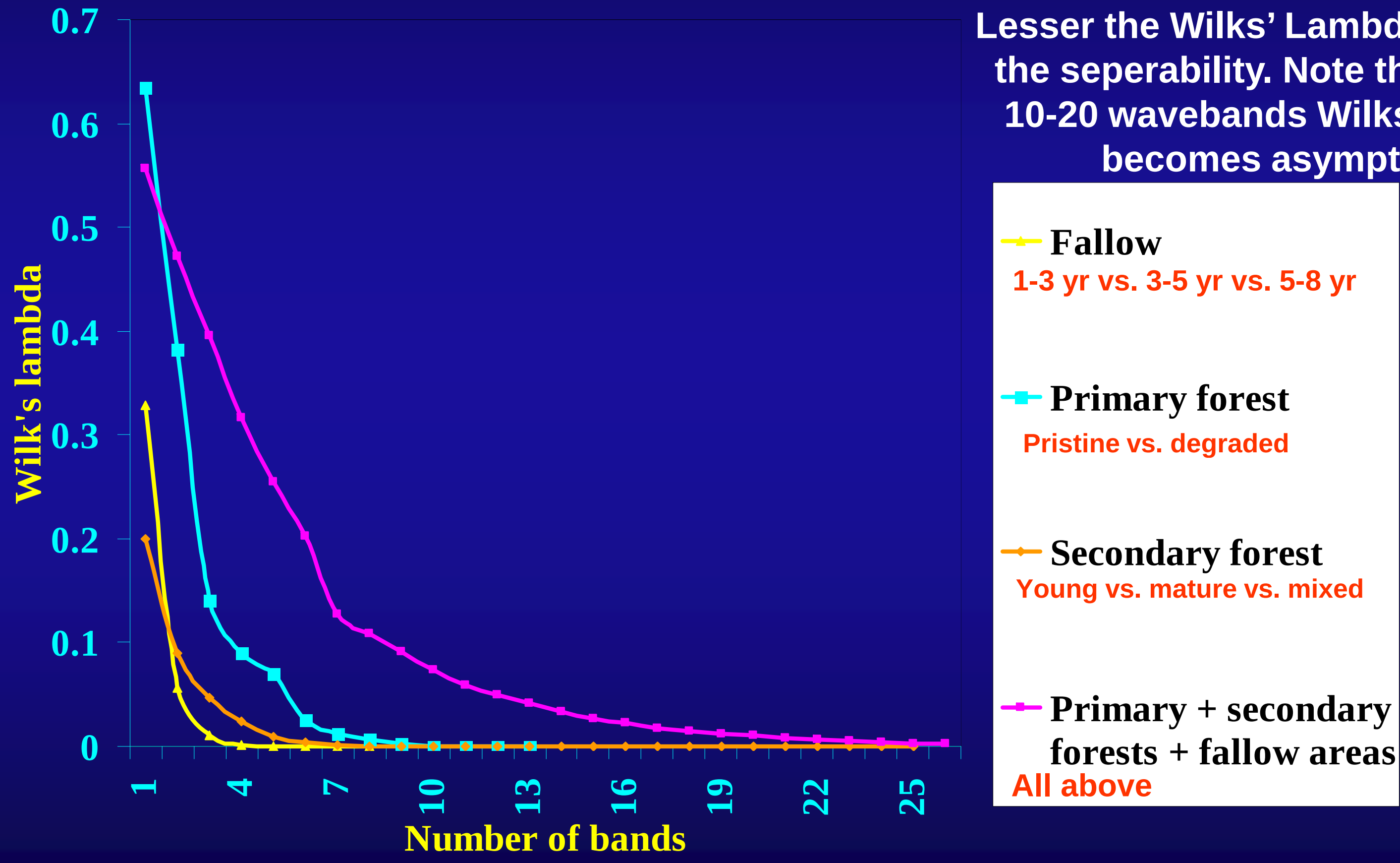


U.S. Geological Survey
U.S. Department of Interior

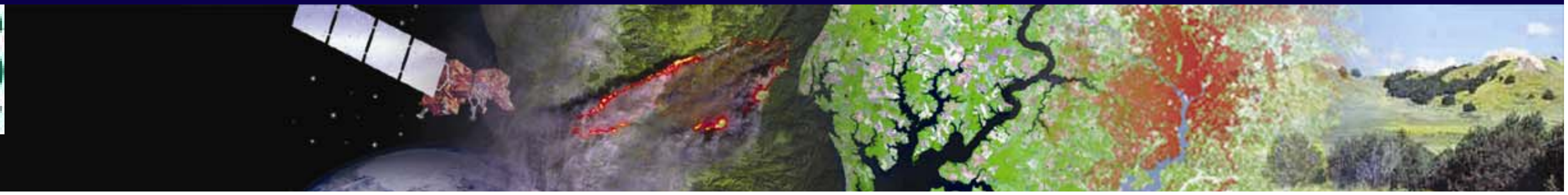
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.3b. 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

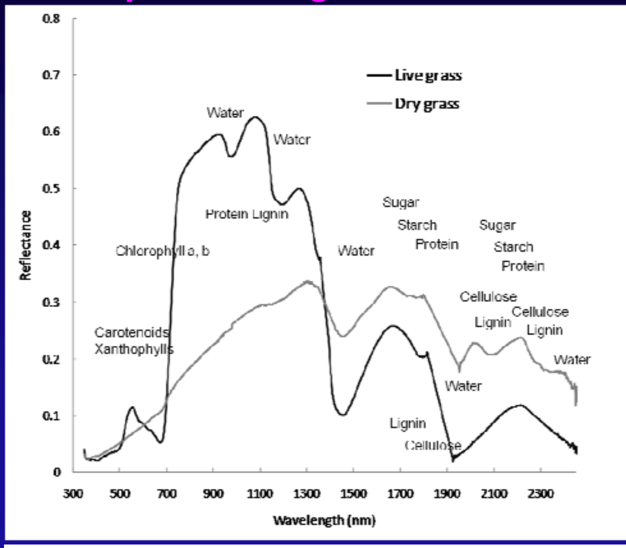


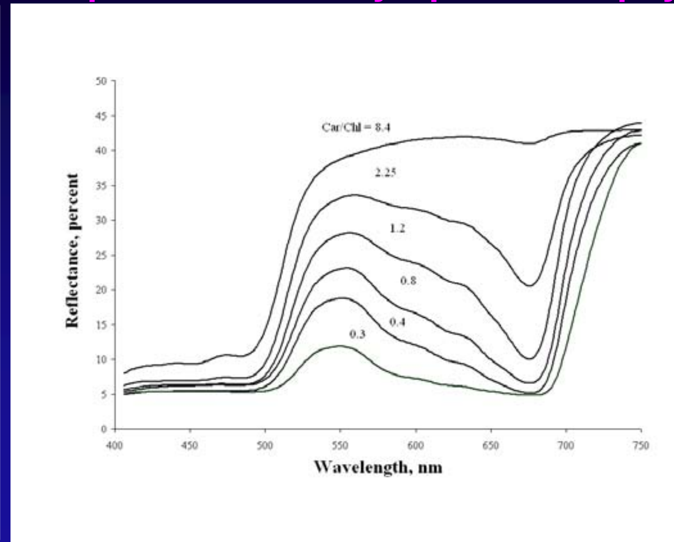
Lesser the Wilks' Lambda greater is the seperability. Note that beyond 10-20 wavebands Wilks' Lambda becomes asymptotic.

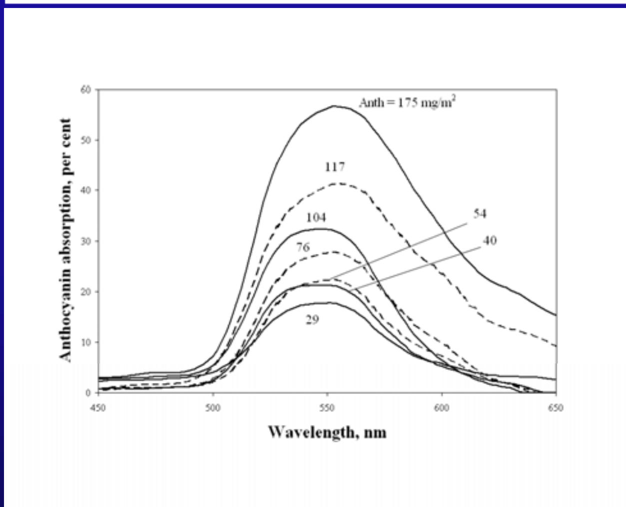


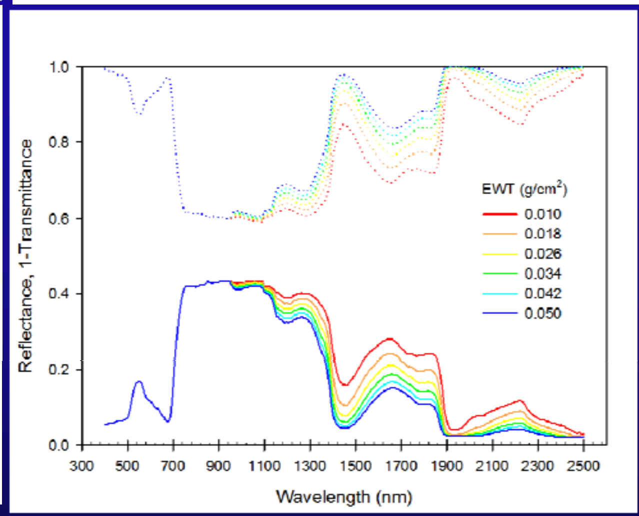
Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.4a. Specific Targeted Portions of the Spectrum to Study Specific Biophysical and Biochemical quantity







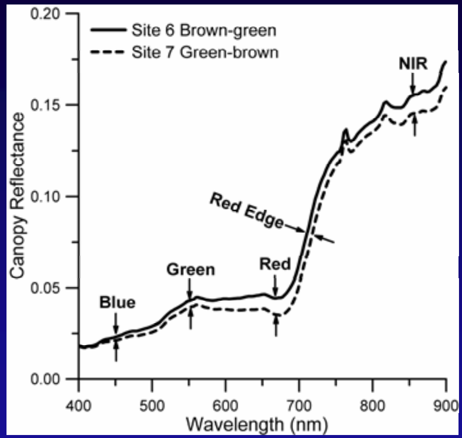


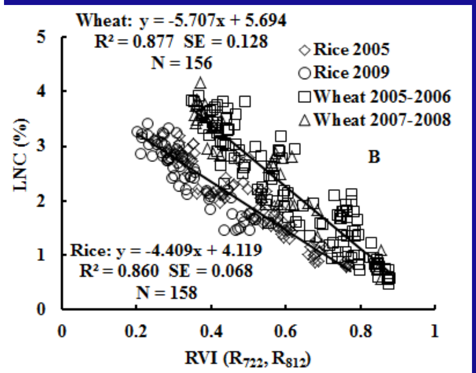
It is also important to know what specific wavebands are most suitable to study particular biophysical and/or biochemical properties. As examples, plant moisture sensitivity is best studied using a narrowband (5 nm wide or less) centered at 970 nm, while plant stress assessments are best made using a 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.

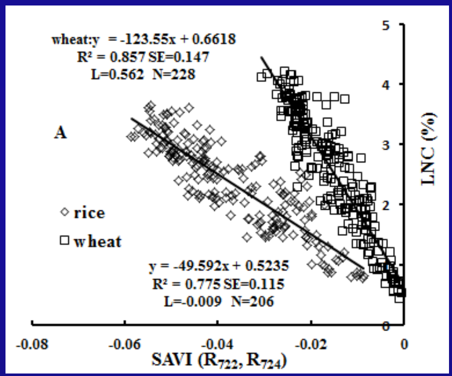
Chapters 6, 9, 10, and 15

Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

1.4b. Specific Targeted Portions of the Spectrum to Study Specific Biophysical and Biochemical quantity



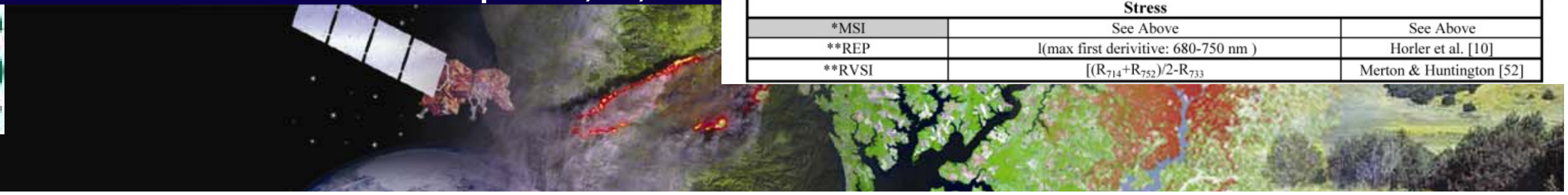




Index	Equation	Reference
Structure (LAI, green biomass, fraction)		
*NDVI	$(R_{NIR}-R_{red})/(R_{NIR}+R_{red})$	Rouse et al.[15]
*SR	R_{NIR}/R_{red}	Jordan [3]
*EVI	$2.5*(R_{NIR}-R_{red})/(R_{NIR}+6*R_{red}-7.5*R_{blue}+1)$	Huete et al.[23]
*NDWI	$(R_{857}-R_{1241})/(R_{857}+R_{1241})$	Gao [29]
**WBI	R_{900}/R_{970}	Peñuelas et al.[28]
*ARVI	$(R_{NIR}-[R_{red}-\gamma*(R_{blue}-R_{red})])/(R_{NIR}+[R_{red}-\gamma*(R_{blue}-R_{red})])$	Kaufman & Tanré [22]
*SAVI	$[(R_{NIR}-R_{red})/(R_{NIR}+R_{red}+L)]*(1+L)$	Huete [21]
**1DL_DGVI	$\sum_{\lambda_{626\,nm}}^{\lambda_{795\,nm}} \lvert R'(\lambda_i)-R'(\lambda_{626\,nm})\rvert \Delta\lambda_i$	Elvidge & Chen [1]
**1DZ_DGVI	$\sum_{\lambda_{626\,nm}}^{\lambda_{795\,nm}} \lvert R'(\lambda_i)\rvert \Delta\lambda_i$	Elvidge & Chen [1]
*VARI	$(R_{green}-R_{red})/(R_{green}+R_{red}-R_{blue})$	Gitelson et al.[13]
*VIgreen	$(R_{green}-R_{red})/(R_{green}+R_{red})$	Gitelson et al.[13]
Biochemical		
Pigments		
**SIPI	$(R_{800}-R_{445})/(R_{800}-R_{680})$	Peñuelas et al. [31]
**PSSR	(R_{800}/R_{675}); (R_{800}/R_{650})	Blackburn [30]
**PSND	$[(R_{800}-R_{675})/(R_{800}+R_{675})]$; $[(R_{800}-R_{650})/(R_{800}+R_{650})]$	Blackburn [32]
**PSRI	$(R_{680}-R_{500})/R_{750}$	Merzlyak et al. [33]
Chlorophyll		
**CARI	$[(R_{700}-R_{670})-0.2*(R_{700}-R_{550})]$	Kim [34]
**MCARI	$[(R_{700}-R_{670})-0.2*(R_{700}-R_{550})]*(R_{700}/R_{670})$	Daughtry et al. [35]
**$CI_{red\ edge}$	$R_{NIR}/R_{red\ edge}-1$	Gitelson et al. [36]
Anthocyanins		
**ARI	$(1/R_{green})-(1/R_{red\ edge})$	Gitelson et al.[40]
**mARI	$[(1/R_{green})-(1/R_{red\ edge})]*R_{NIR}$	Gitelson et al. [36]
**RGRI	R_{red}/R_{green}	Gamon & Surfus [7]
**ACI	R_{green}/R_{NIR}	Van den Berg & Perkins [41]
Carotenoids		
**CRI1	$(1/R_{510})-(1/R_{550})$	Gitelson et al.[42]
**CRI2	$(1/R_{510})-(1/R_{700})$	Gitelson et al. [42]
Water		
*NDII	$(R_{NIR}-R_{SWIR})/(R_{NIR}+R_{SWIR})$	Hunt & Rock [12]
*NDWI, **WBI	See Above	See Above
*MSI	R_{SWIR}/R_{NIR}	Rock et al. [43]
Lignin &Cellulose/Residues		
**CAI	100*[0.5*(R2031+R2211)-R2101]	Daughtry [47]
**NDLI	$[\log(1/R_{1754})-\log(1/R_{1680})]/[\log(1/R_{1754})+\log(1/R_{1680})]$	Serrano et al. [48]
Nitrogen		
**NDNI	$[\log(1/R_{1510})-\log(1/R_{1680})]/[\log(1/R_{1510})+\log(1/R_{1680})]$	Serrano et al. [48]
Physiology		
Light Use Efficiency		
RGRI,SIPI	See Above	See Above
**PRI	$(R_{530}-R_{570})/(R_{530}+R_{570})$	Gamon et al. [9]
Stress		
*MSI	See Above	See Above
**REP	l(max first derivitive: 680-750 nm)	Horler et al. [10]
**RVSI	$[(R_{714}+R_{752})/2-R_{733}]$	Merton & Huntington [52]

<u>Note</u>: Narrowbands targeted to study specific vegetation biophysical and biochemical variable: Each waveband in Table 28.1 was uniquely targeted to study specific vegetation biophysical, and biochemical properties and\or captures specific events such as plant stress. For example, a waveband centered at 550 nm provides excellent sensitivity to plant nitrogen, a waveband centered at 515 nm is best for pigments (carotenoids, anthocyanins), and a waveband centered at 970 nm or 1245 nm was ideal to study plant moisture fluctuations;

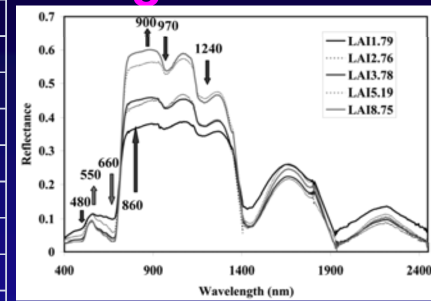
Chapters 8, 14, 21



Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

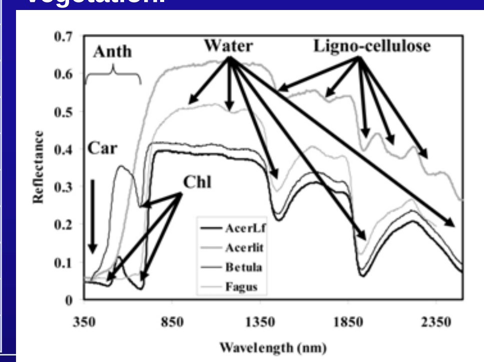
2.1a. Thirty-three (33) Optimal Bands in Study of Vegetation

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 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;

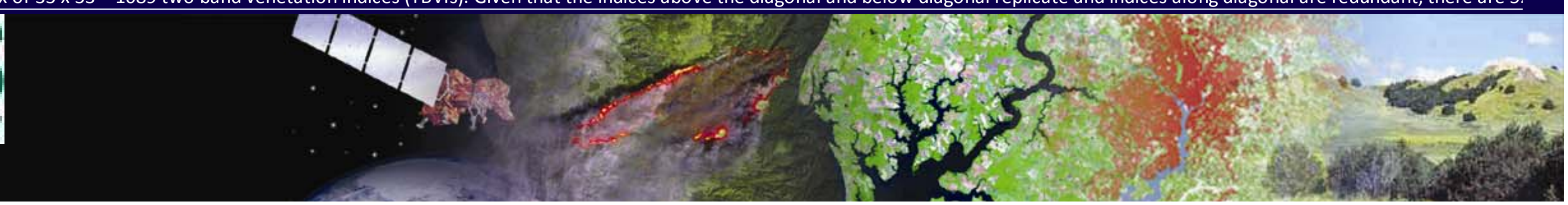
** = when there were close wavebands (e.g., 960 nm, 970 nm), only one waveband (e.g., 970 nm) was selected based on overwhelming eveidence as reported in various chapters. This would avoid redundancy.

*** = 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

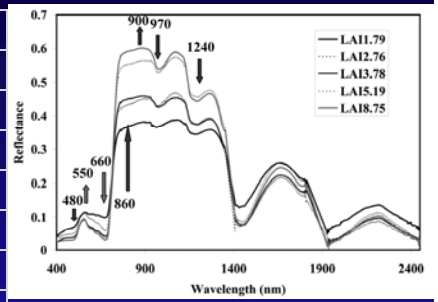
USGS science for a changing world



Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

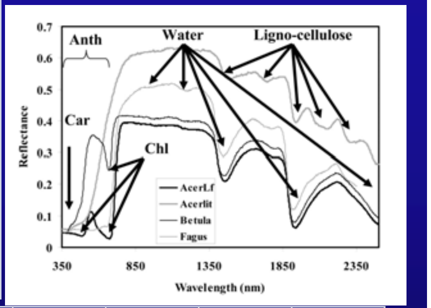
2.1b. Thirty-three (336) Optimal Bands in Study of Vegetation

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:

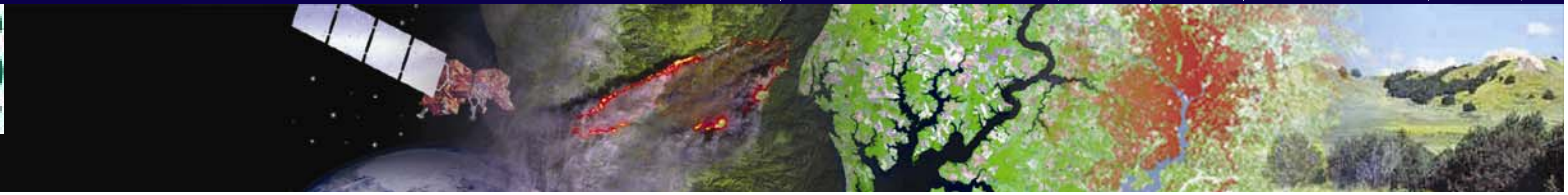
* = wavebands were selected based on research and discussions in the chapters;

** = 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.

*** = 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.

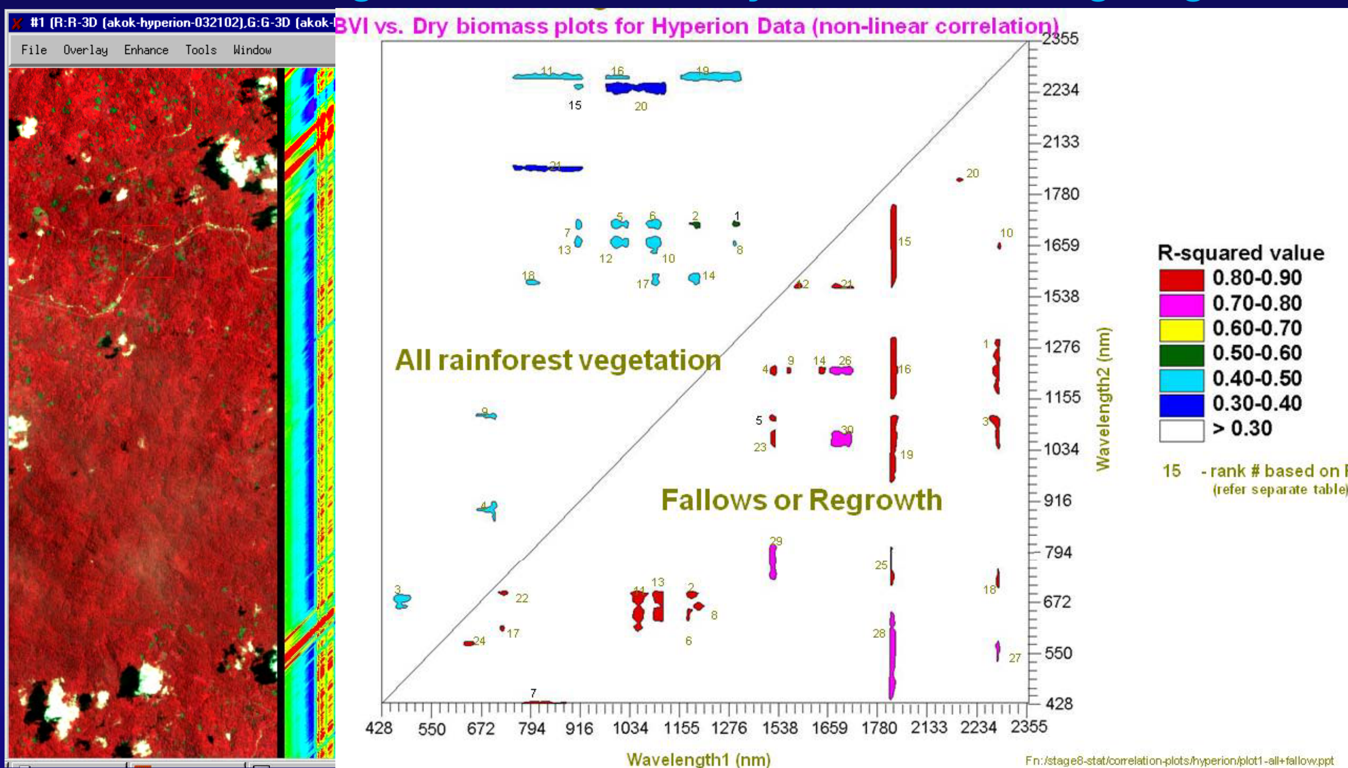
***** = 33 wavebands lead to a matrix of 33 x 33 = 1089 two band vehetation indices (TBVIs). Given that the indices above the diagonal and below diagonal replicate and indices along diagonal are redundant, there are 5



Knowledge Gain in using Hyperspectral Narrowband Data in Study of Vegetation

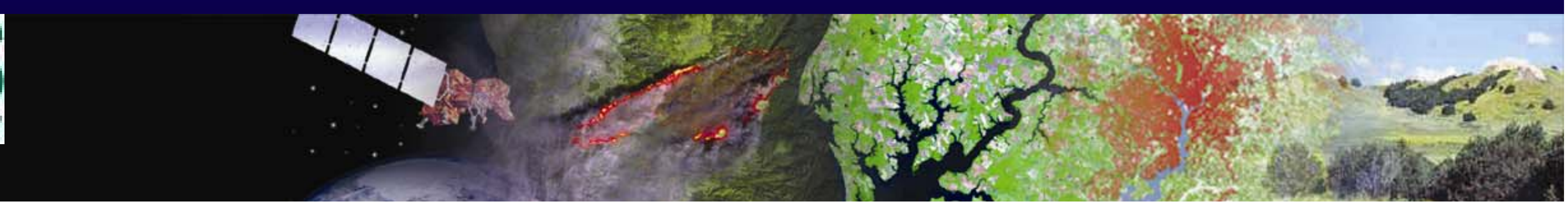
3.1a. Advances in Methods and Approaches

e.g., Data Redundancy and overcoming Hughes Phenomenon



<u>Note 1</u>: 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 (Table 28.1) to study vegetation

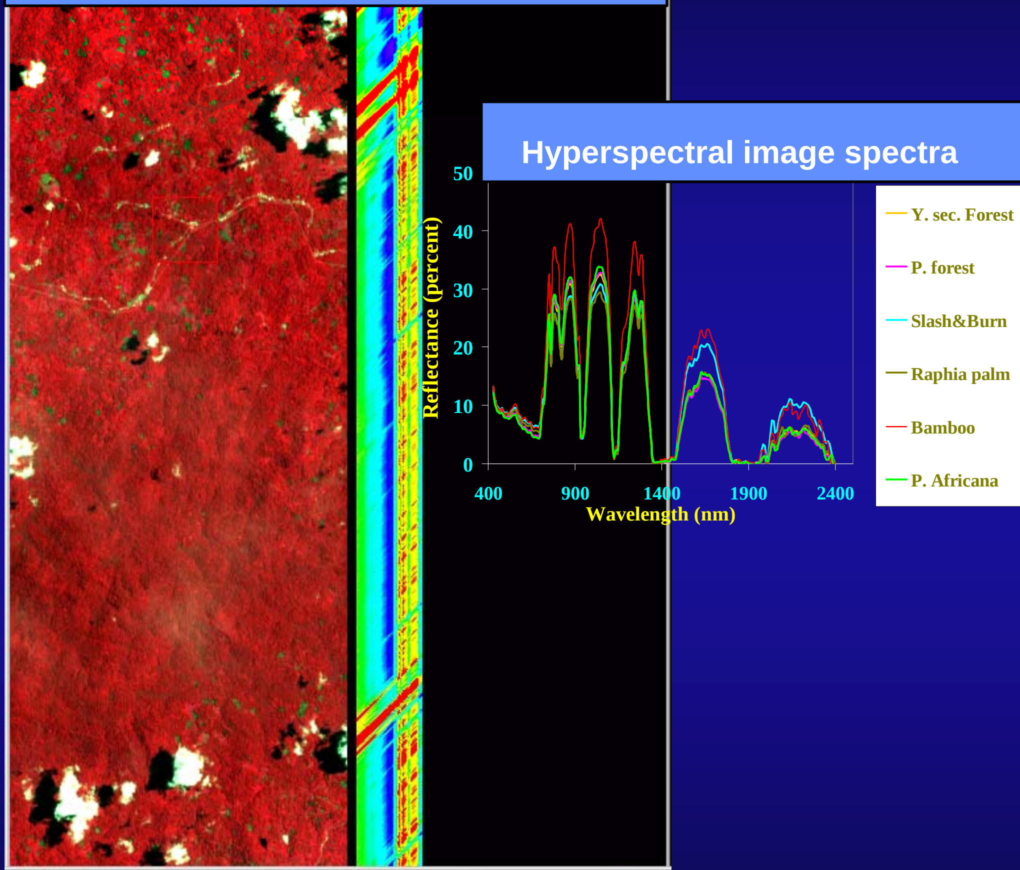
<u>Note 2</u>: The large number of hyperspectral narrowbands and derived hyperspectral vegetation indices (HVIs) offer far greater opportunities in finding an appropriate index for studying a given vegetation variable when compared to broadband data. However, as we already know, a large number of these wavebands are redundant in studying of vegetation. So, selection of non-redundant optimal wavebands to study a wide array of vegetation biophysical and biochemical properties was explored.



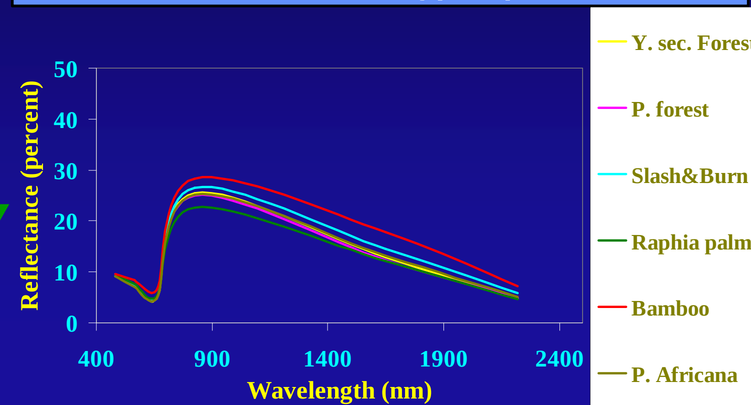
Hyperspectral Narrowband Sensors (imaging Spectroscopy) Generating data for other Sensors?

Processing acquired hyperspectral data into other types of data

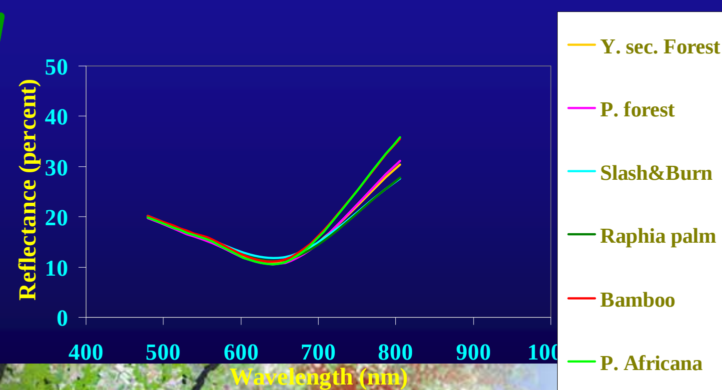
Hyperspectral image data cube



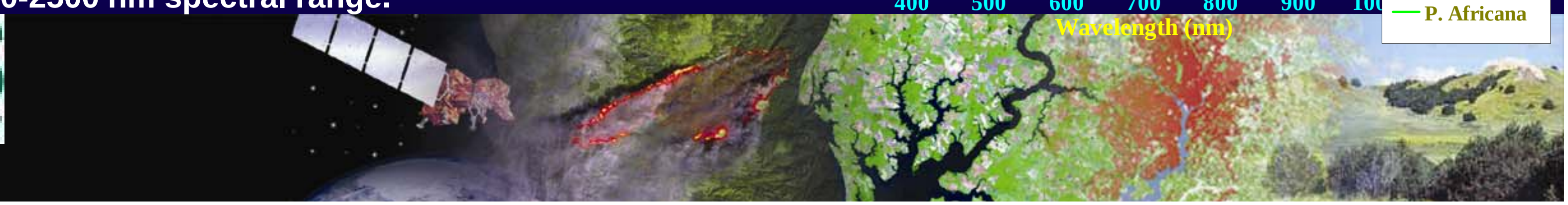
Generated Landsat ETM+ for data continuity: 6 non-thermal broadbands at 30 m of Landsat ETM+ Generated from a Hyperspectral Sensor



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



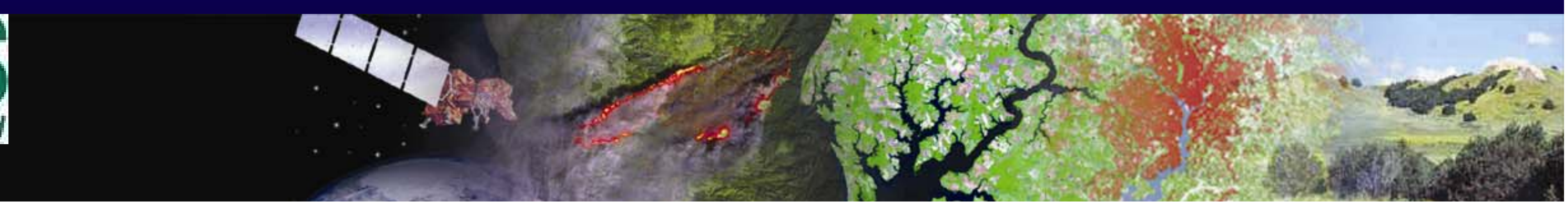
Imaging spectroscopy: 242 hyperspectral bands, each of 5 or 10 nm wide, in 400-2500 nm spectral range.



Knowledge Gap in using Hyperspectral Narrowband Data in Study of Vegetation

Opportunities for Future Research

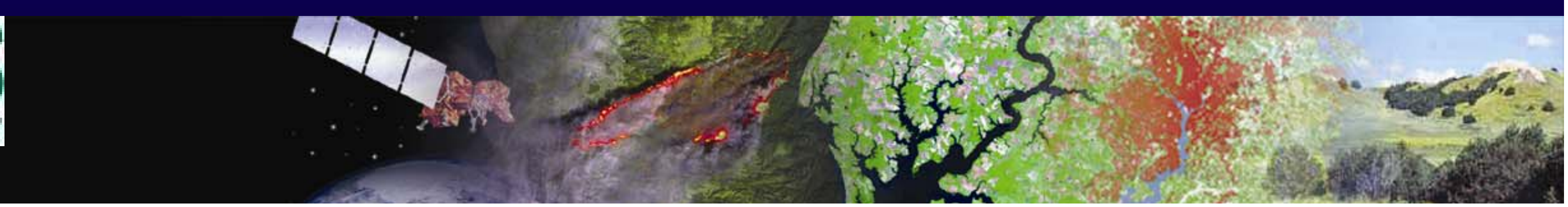
1. **New Hyperspectral Vegetation indices (HVIs): huge scope exists in developing target specific HVIs for vegetation biophysical and biochemical modeling;**
2. **New Multi-band Vegetation Indices (MBVIs): hyperspectral narrowband data should help us develop MBVIs for vegetation biophysical and biochemical modeling;**
3. **Increased vegetation\crop class accuracies: Multiple Hyperspectral bands for increased accuracies in classification of vegetation types, species types, crop types;**
4. **Overcome uncertainties in vegetation\crop classification: in studying complex tropical forest canopies that have diverse overstory, understory, and background influences;**
5. **Improved vegetation\crop class separation: specific hyperspectral narrowbands will help separate crop types, vegetation types, and vegetation species.**



Knowledge Gap in using Hyperspectral Narrowband Data in Study of Vegetation

Opportunities for Future Research

6. **Minimize\eliminate data redundancy:** for achieving effective crop\vegetation models and maps;
7. **Determine optimal bands:** for studying different crops\vegetation;
8. **Establish methods for whole spectral analysis:** develop spectral library, develop methods like spectral matching techniques.



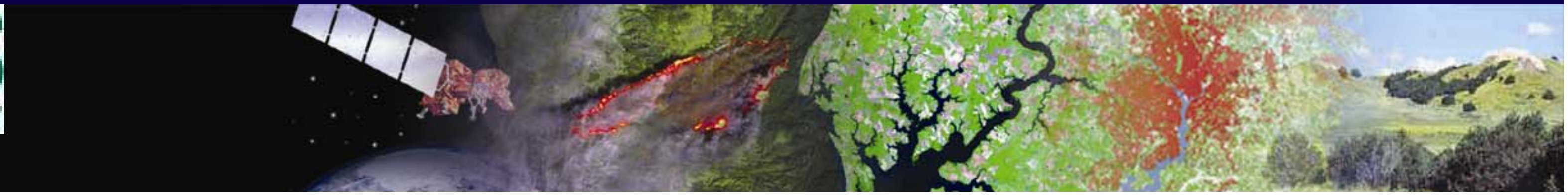
Knowledge Gap in using Hyperspectral Narrowband Data in Study of Vegetation

Upcoming Spaceborne Hyperspectral Sensors

The 4 near future hyperspectral spaceborne missions:

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

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

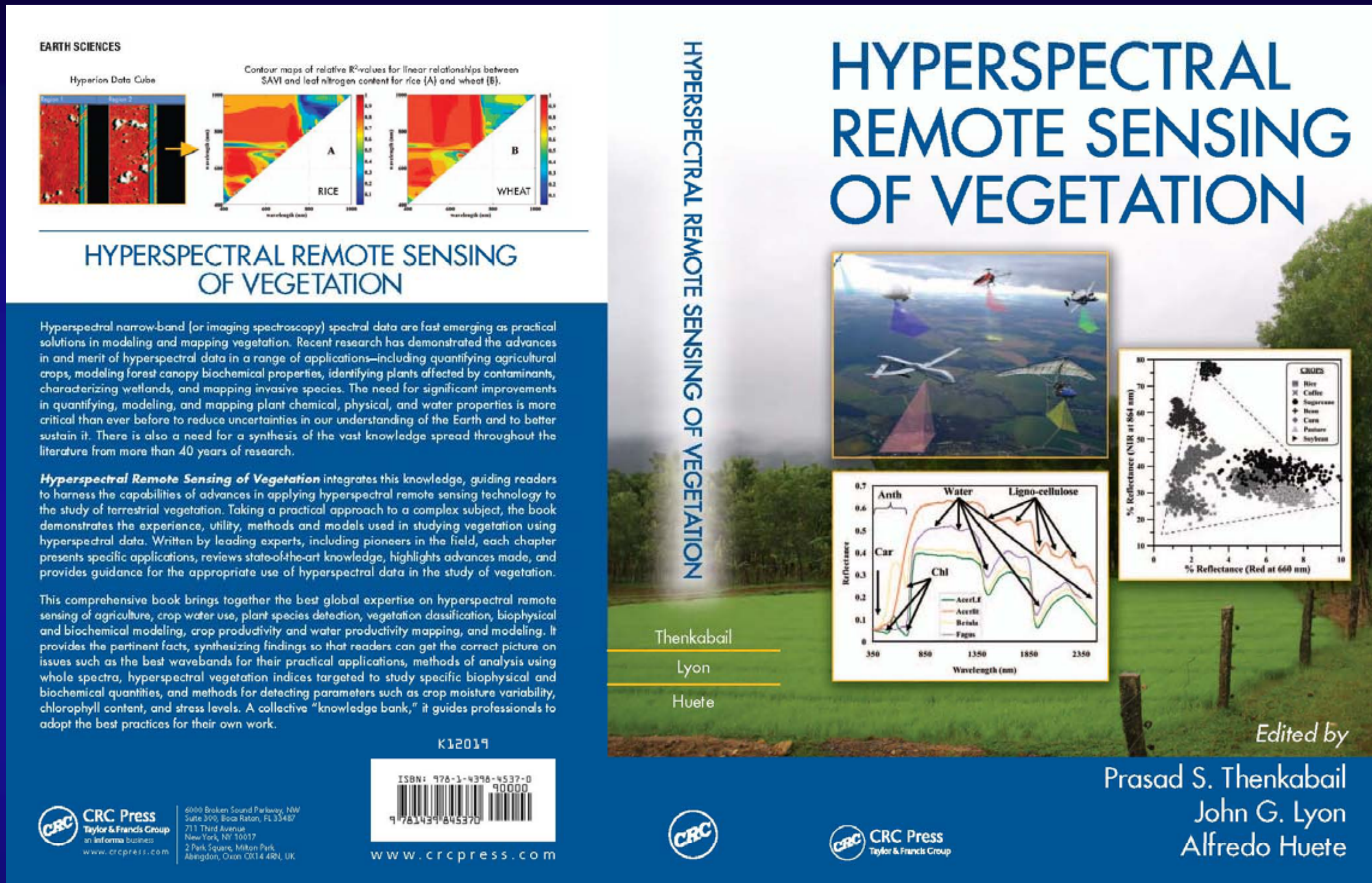


Publications

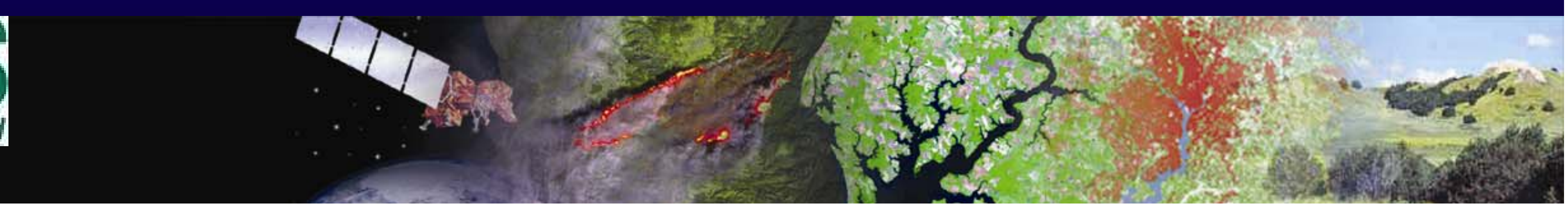
Hyperspectral Remote Sensing of Vegetation

Hyperspectral Remote Sensing Vegetation

References Pertaining to this Presentation



Thenkabail, P.S., Lyon, G.J., and Huete, A. 2011. Book entitled: "Hyperspectral Remote Sensing of Vegetation". 28 Chapters. CRC Press- Taylor and Francis group, Boca Raton, London, New York. Pp. 700+ (80+ pages in color). To be published by October 31, 2011.



Hyperspectral Remote Sensing Vegetation

References Pertaining to this Presentation

1. Thenkabail, P.S., Enclona, E.A., Ashton, M.S., Legg, C., Jean De Dieu, M., 2004. Hyperion, IKONOS, ALI, and ETM+ sensors in the study of African rainforests. Remote Sensing of Environment, 90:23-43.

2. Thenkabail, P.S., Enclona, E.A., Ashton, M.S., and Van Der Meer, V. 2004. Accuracy Assessments of Hyperspectral Waveband Performance for Vegetation Analysis Applications. Remote Sensing of Environment, 91:2-3: 354-376.

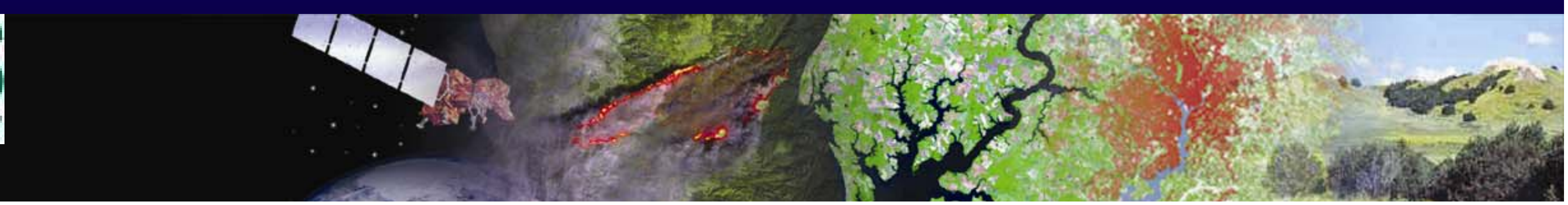
3. Thenkabail, P.S. 2003. Biophysical and yield information for precision farming from near-real time and historical Landsat TM images. International Journal of Remote Sensing. 24(14): 2879-2904.

4. Thenkabail P.S., Smith, R.B., and De-Pauw, E. 2002. Evaluation of Narrowband and Broadband Vegetation Indices for Determining Optimal Hyperspectral Wavebands for Agricultural Crop Characterization. Photogrammetric Engineering and Remote Sensing. 68(6): 607-621.

5. Thenkabail, P.S., 2002. Optimal Hyperspectral Narrowbands for Discriminating Agricultural Crops. Remote Sensing Reviews. 20(4): 257-291.

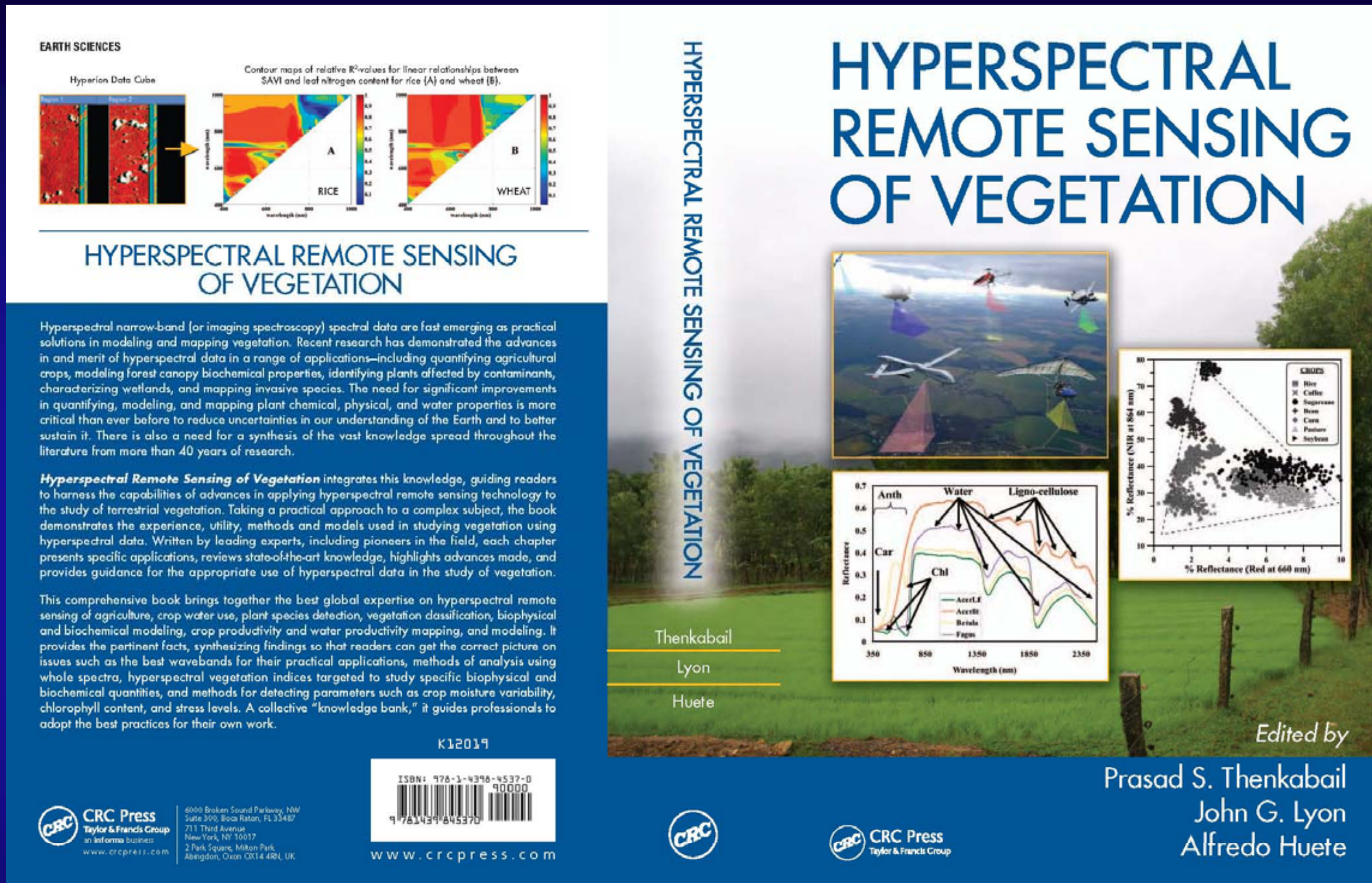
6. Thenkabail P.S., Smith, R.B., and De-Pauw, E. 2000b. Hyperspectral vegetation indices for determining agricultural crop characteristics. Remote sensing of Environment. 71:158-182.

7. Thenkabail P.S., Smith, R.B., and De-Pauw, E. 1999. Hyperspectral vegetation indices for determining agricultural crop characteristics. CEO research publication series No. 1, Center for earth Observation, Yale University. Pp. 47. Book:ISBN:0-9671303-0-1. (Yale University, New Haven).

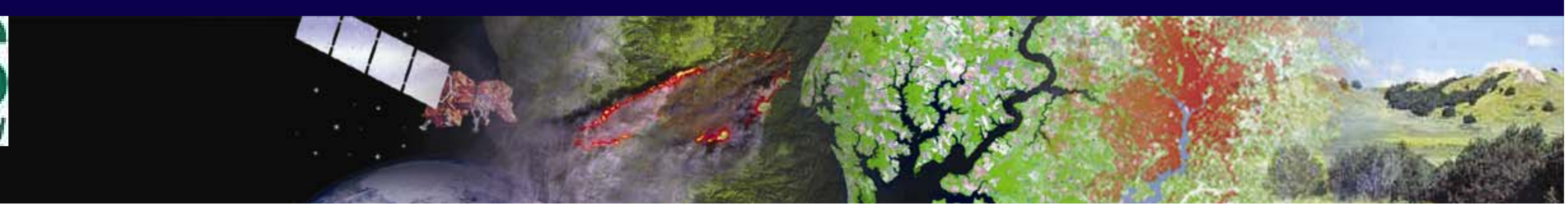


Hyperspectral Remote Sensing Vegetation

References Pertaining to this Presentation



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



Hyperspectral Remote Sensing Vegetation

Note to Workshop Participants

The materials presented in this workshop are strictly for use by the workshop participants and <u>should not be used anywhere</u> without the written permission from the main presenter: Prasad Thenkabail or John Lyon or Dean Riley.

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