Remote Sensing for Agricultural Applications: Principles and Techniques (2023-2024)

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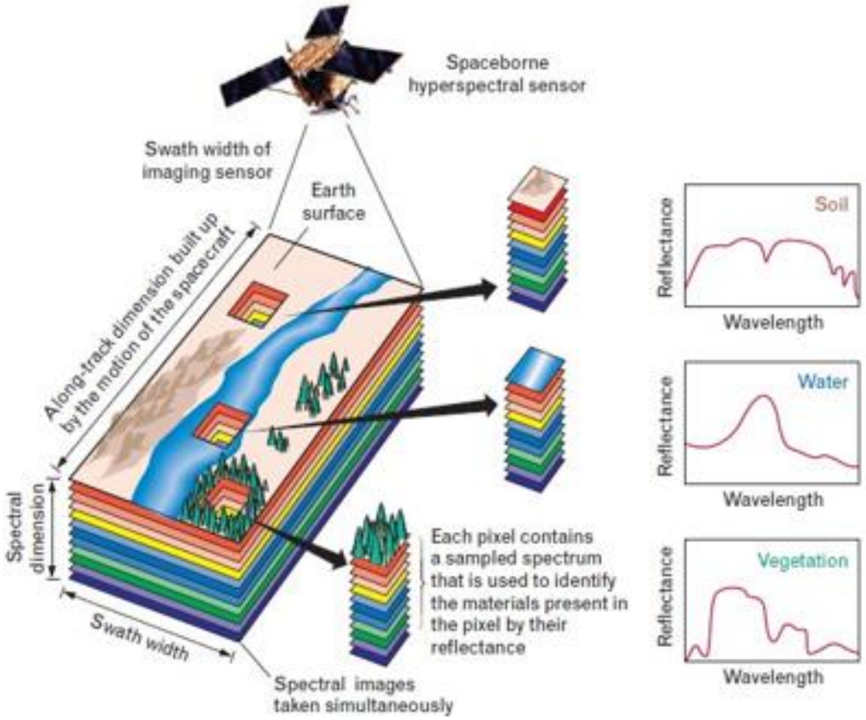
Lecture 9: Hyperspectral remote sensing



December 20, 2022

Outline

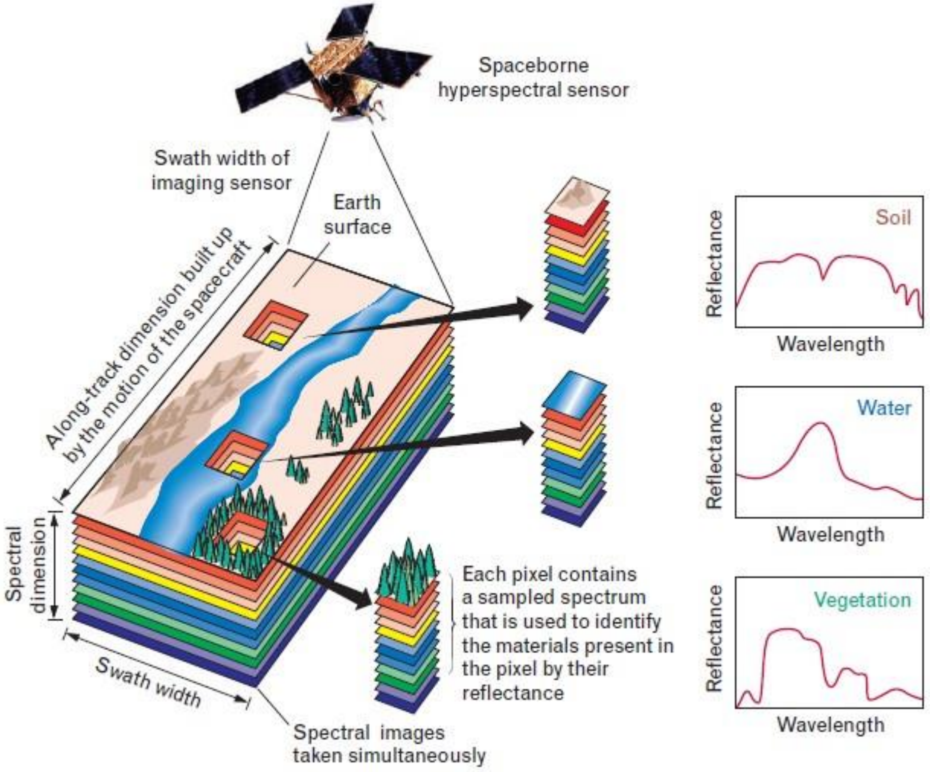
- Introduction to hyperspectral remote sensing
- Hyperspectral analysis techniques
    1. Dimensionality reduction
    2. Spectral similarity
    3. Spectral mixture analysis
    4. Spectral indices
    5. Continuum removal
    6. Spectral derivative
    7. Wavelet analysis
- Purpose:
    – to learn about major research topics in the field of hyperspectral remote sensing
    – to understand what can be done with hyperspectral data

Concepts

- Spectroscopy
  - "Spectroscopy is the study of light as a function of wavelength that has been emitted, reflected or scattered from a solid, liquid, or gas." (Clark, 1999)

- Spectroscopy of vegetation

- Imaging spectroscopy
  - a new tool that can be used to map specific
    materials by detecting
    specific chemical bonds. (USGS Spectroscopy Lab)



Shaw & Burke (2003)

Clark, R. N., Chapter 1: Spectroscopy of Rocks and Minerals, and Principles of Spectroscopy, in *Manual of Remote Sensing, Volume 3, Remote Sensing for the Earth Sciences*, (A.N. Rencz, ed.) John Wiley and Sons, New York, p 3-58, 1999.

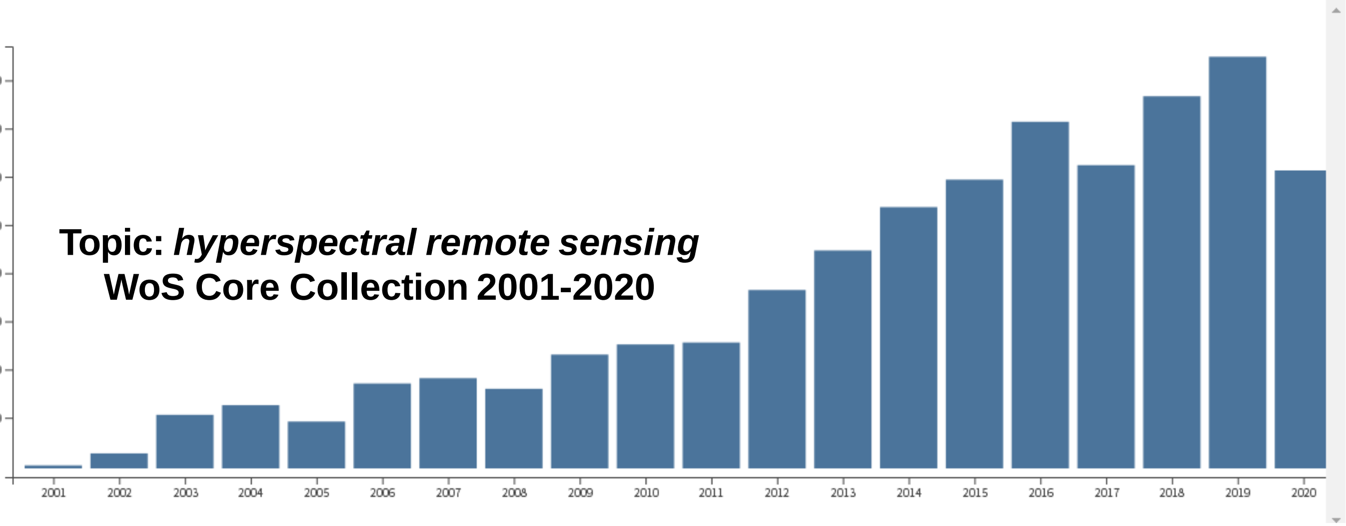
History of hyperspectral RS

(Figure from Goetz, 2009, RSE)

- The First Portable Field Reflectance Spectrometer, 1974

Total Publications
9,113 Analyze

Published HRS articles each year



AVIRIS
Airborne Visible / Infrared Imaging Spectrometer

- Airborne instrument: First flight with AVIRIS, 1987

- The Portable Field Spectroradiometer, 2010s

Hyperspectral instruments

- We need more satellite hyperspectral instruments. Some countries are working on their hyperspectral missions.

Airborne instruments

TABLE 1. PARAMETERS OF EIGHT HYPERSPECTRAL

PARAMETER	HYDICE	AVIRIS
Altitude (km)	1.6	20
Spatial resolution (m)	0.75	20
Spectral resolution (nm)	7–14	10
Coverage (μm)	0.4–2.5	0.4–2.5
Number of bands	210	224
Data cube size (sample × lines × bands)	200 × 320 × 210	512 × 614 × 224

Bioucas-Dias et al. (2013)

Spaceborne instruments

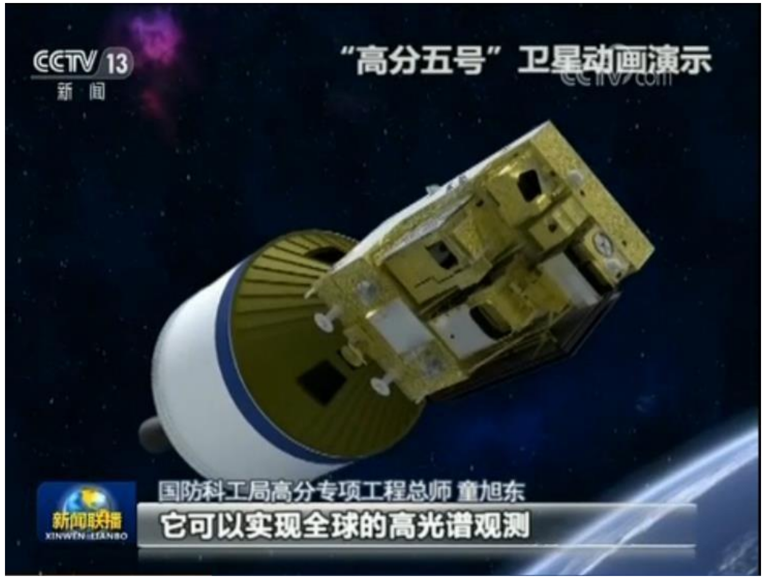
TABLE 1. THE MAIN PARAMETERS OF ON-ORBIT AND PLANNED SPACEBORNE HYPERSPECTRAL SENSORS.

SATELLITE PAYLOAD	EO-1/ HYPERION	*PROJECT FOR ON-BOARD AUTONOMY (PROBA)-1* CHRIS	*GAOFEN-5* AHSI	DESIS	HYSIS	PRISMA HSI	ENMAP HSI	*ADVANCED LAND OBSERVING SATELLITE (ALOS)-3* HISUI
Nation	United States	European Space Agency	China	Germany	India	Italy	Germany	Japan
Launch date	2000 (terminated in 2017)	2001	May 2018	August 2018	November 2018	March 2019	~2020	~2019
Orbit altitude (km)	705	550~670	705	400	630	615	652	626
Spectral range (μm)	0.4~2.5	0.4~1.05	0.39~2.51	0.4–1	0.4–2.5	0.4–2.5	0.42–2.45	0.4–2.5
Total number of bands	220	62	330	235	70 + 256	239	>240	185
Spectral resolution (nm)	10	1.25~11	5 (VNIR), 10 (SWIR)	2.55	10	<12	6.5 (VNIR), 10 (SWIR)	10 (VNIR), 12.5 (SWIR)
Ground sample distance (m)	30.38	17/34	30	30	30	30	30	30
Swath width (km)	7.7	13~15	60	30	30	30	30	30
Dispersive systems	Grating	Prism	Grating	Grating	–	Prism	Prism	Grating

Liu et al. (2019)

Q1: why are hyperspectral satellite instruments fewer than multispectral ones?

China’s Gaofen-5



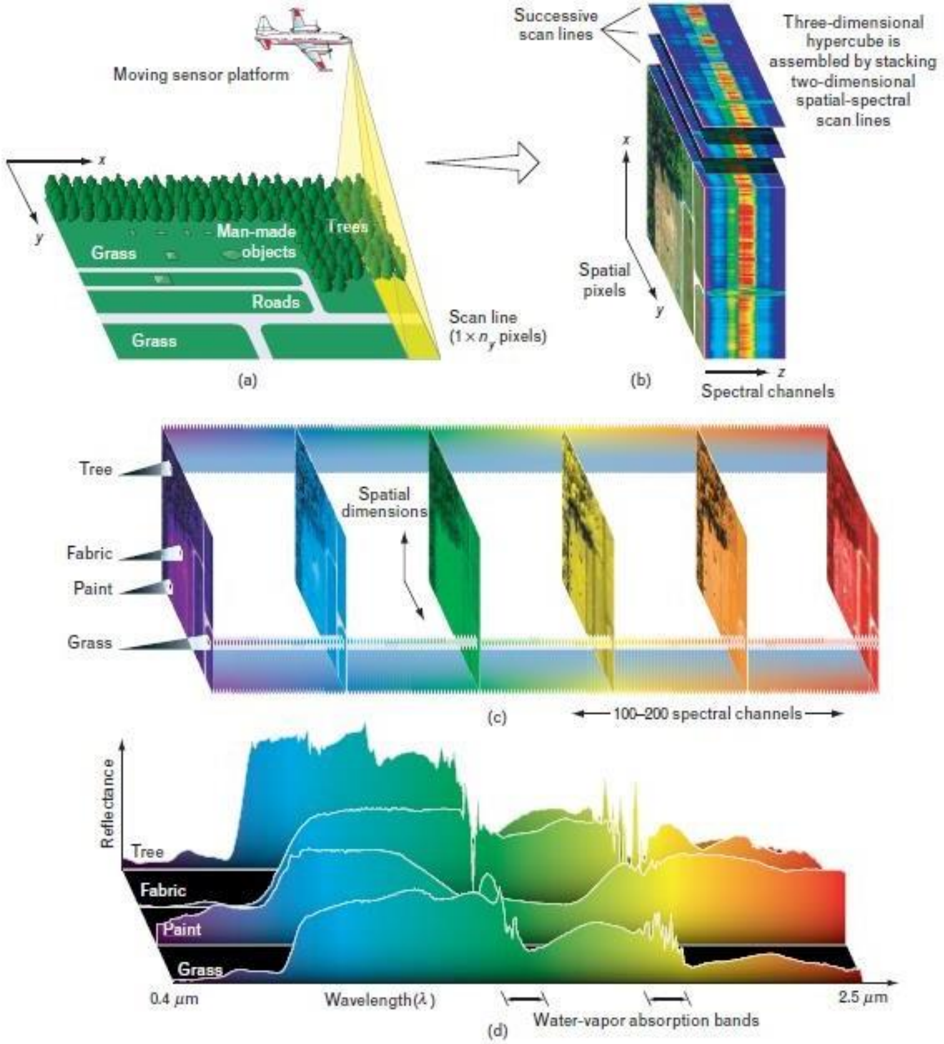
Acronym	Full name
AIUS	Atmospheric Infrared Ultra-spectral spectrometer
DPC	Directional Polarization Camera
EMI	Environment Monitoring Instrument
GMI	Greenhouse-gases Monitoring Instrument
AHSI	Advanced Hyperspectral Imager
VIMS	Visual and Infrared Multispectral Sensor

- Launch date of **GF-5/01**: May 8, 2018 ; Launch date of **GF-5/02**: Sep 7, 2021
- The world's first full-spectrum hyperspectral satellite for comprehensive observation of the **atmosphere** and **land**
- Equipped with six advanced observation payloads, such as shortwave infrared hyperspectral camera and a greenhouse gas detector
- AHSI: Advanced Hyperspectral Imager (Land observation)
  - Wavelength range: 0.4-2.5 µm; Spectral resolution: 5/10 nm; 320 bands
  - Swath: 60 km; spatial resolution: 30 m

Hyperspectral data

- Disadvantages of hyperspectral data:
  - *Large data volume*
  - *Collinearity between bands*

- Advantages of hyperspectral data
  - *Detailed spectral information*
  - *Characterization of absorption features*



Shaw & Burke (2003)

1. Dimensionality reduction

- Data dimensionality
  - Dimensionality is the number of spectral bands
  - Neighboring bands are highly correlated
  - Can be reduced in order to increase data processing efficiency and decrease storage space

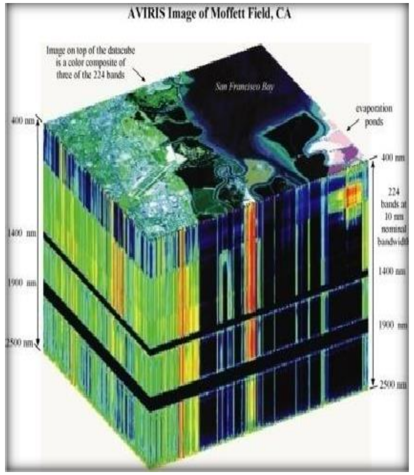
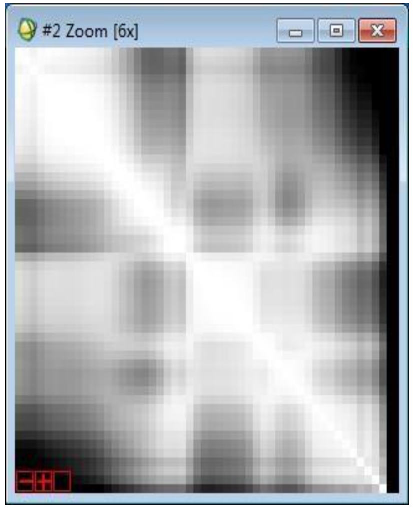


Figure from Jensen (2006)



A correlation matrix

Dimensionality reduction

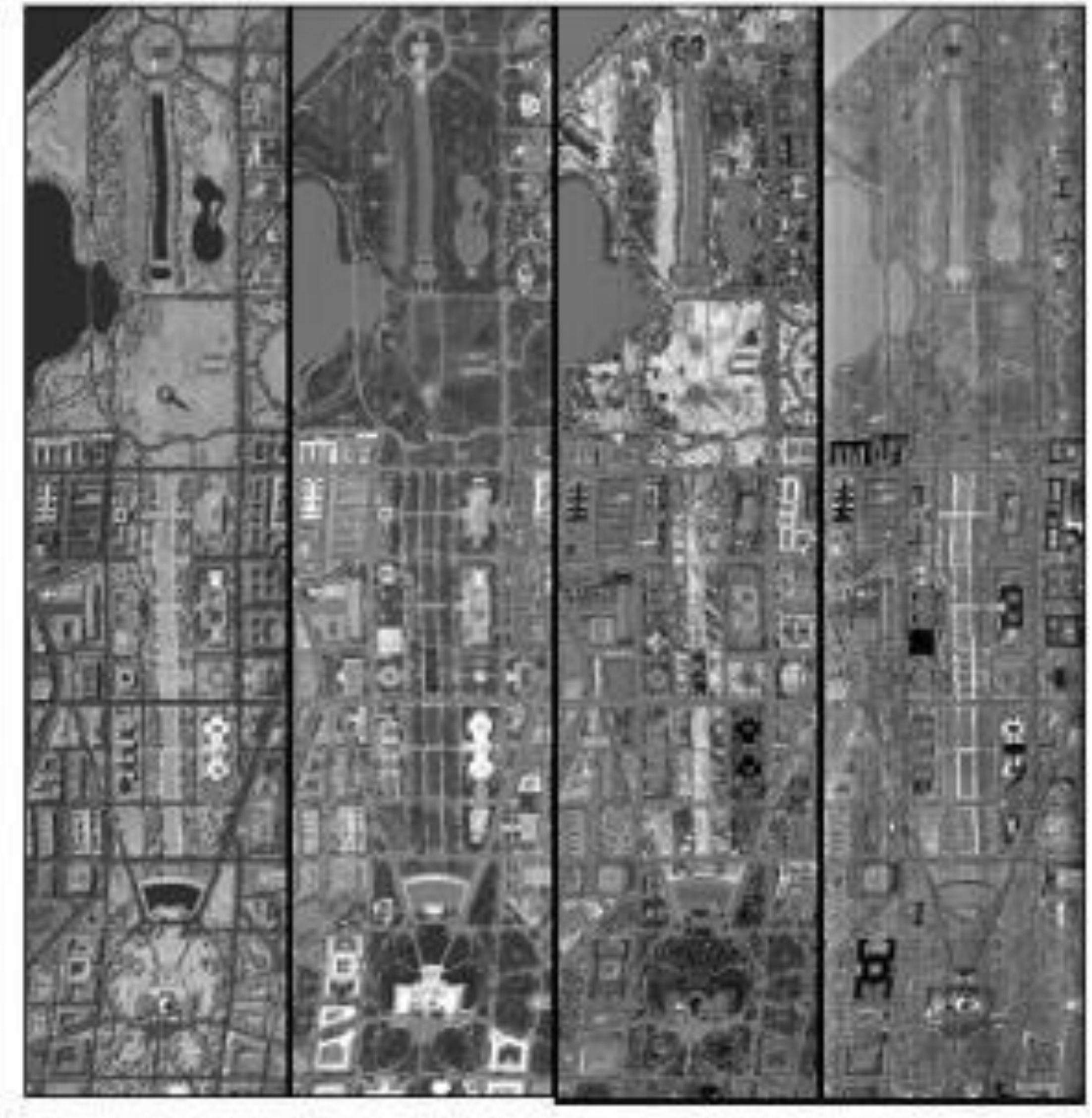
- Band selection (output: bands)
  - Select a subset of spectral bands
  - Sequential Forward Selection (SFS)
  - Sequential Backward Selection (SBS)
  - Sequential Forward Floating Selection (SFFS)

- Feature extraction (output: features)
  - Extract a small number of new spectral features from original bands
  - Principal component analysis (PCA)
  - Minimum noise fraction transformation (MNF)
  - Wavelet transform

Q2: what is the difference between band selection and feature extraction?

Example: PCA

False color composite of Washing D.C. USA



Benediktsson et al. (2005), TGRS, 43, 480-491.

2. Similarity measures

- How to compare pixel spectra?
- A measure of similarity between two spectra in k-dimensional space
- Spectral angle mapper (SAM):

$$D_{SAM}(X,Y) = \alpha\cos\left(\frac{\sum_{i=1}^{K} x_i y_i}{\sum_{i=1}^{K} x_i^2 \sum_{i=1}^{K} y_i^2}\right)$$

x_i and y_i are two spectra with k bands, respectively.

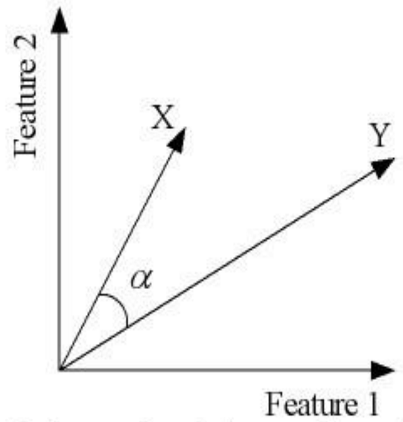


Figure 1. Spectral angle in two-dimensional space.

Similarity measures

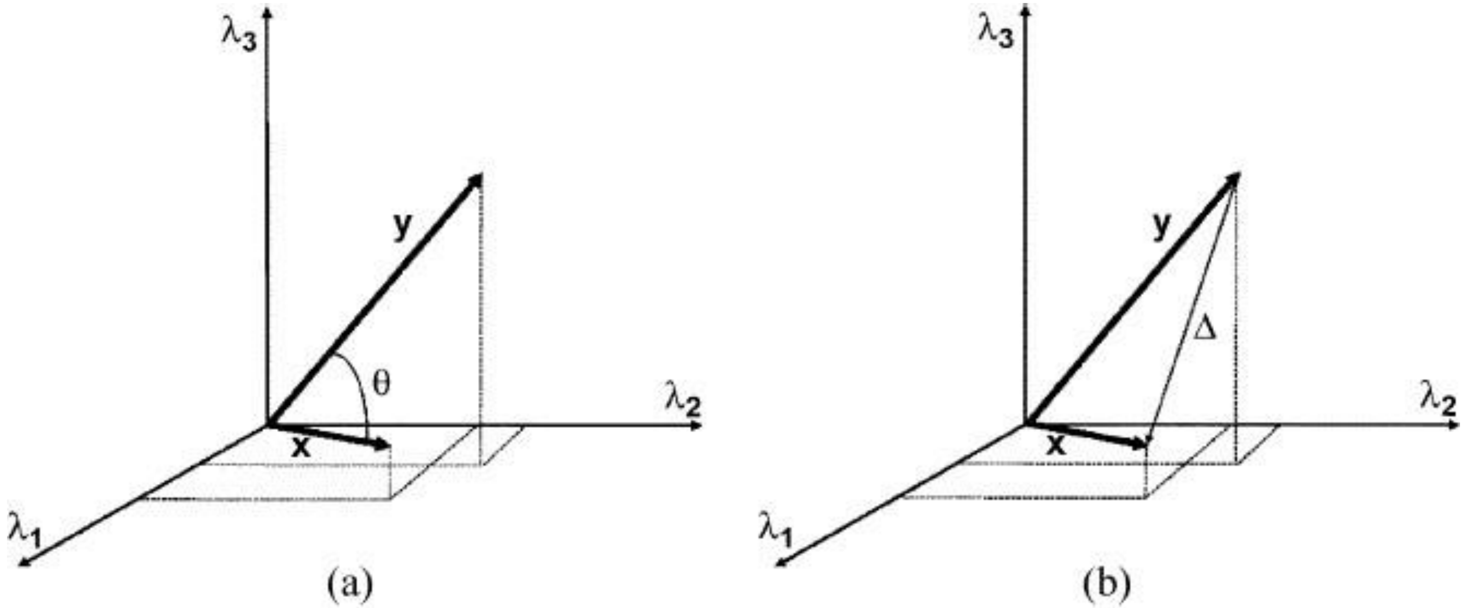


Fig. 2. Two distance metrics used in hyperspectral processing. (a) SAM, θ. (b) EMD, Δ.

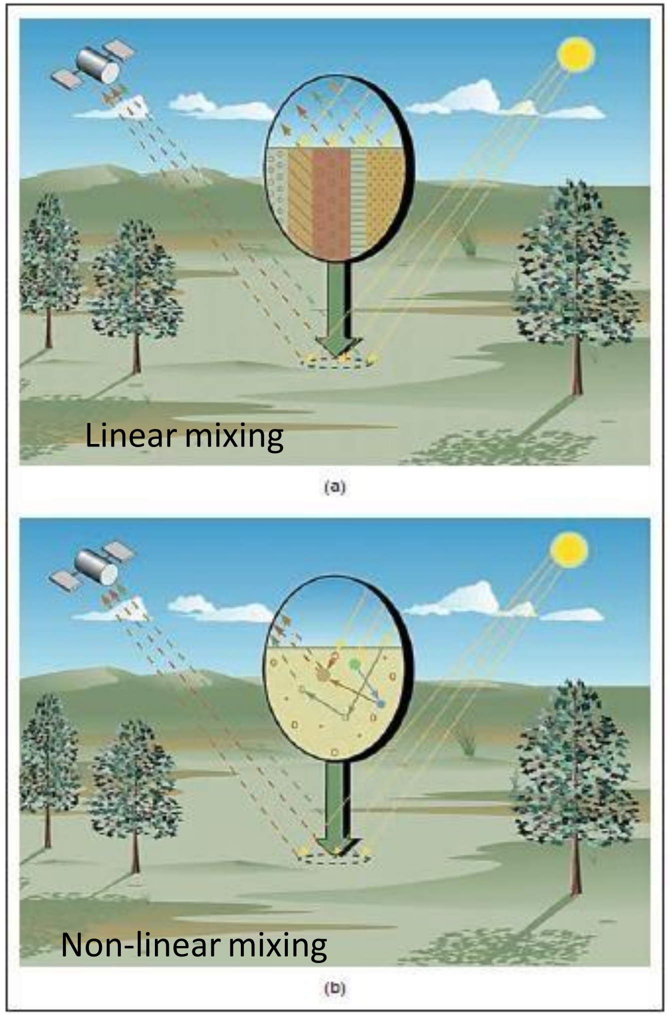
- SAM: angle-based distance between two vectors
- EMD: Euclidean distance between two vectors

3. Spectral mixing

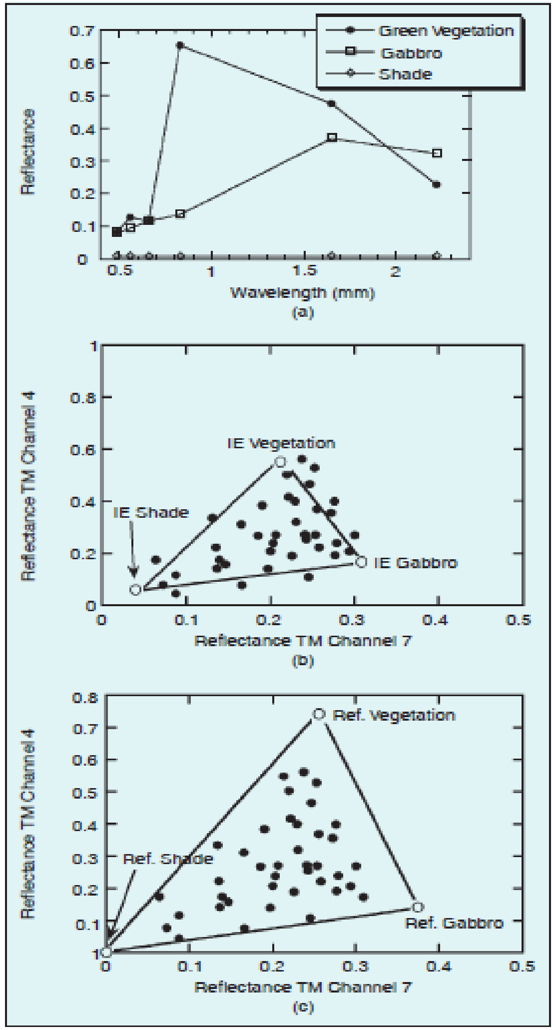
- Why care about spectral mixing and spectral unmixing?

- The signal for a single pixel may come from many surface materials.

- There are a lot of mixed pixels in an image.

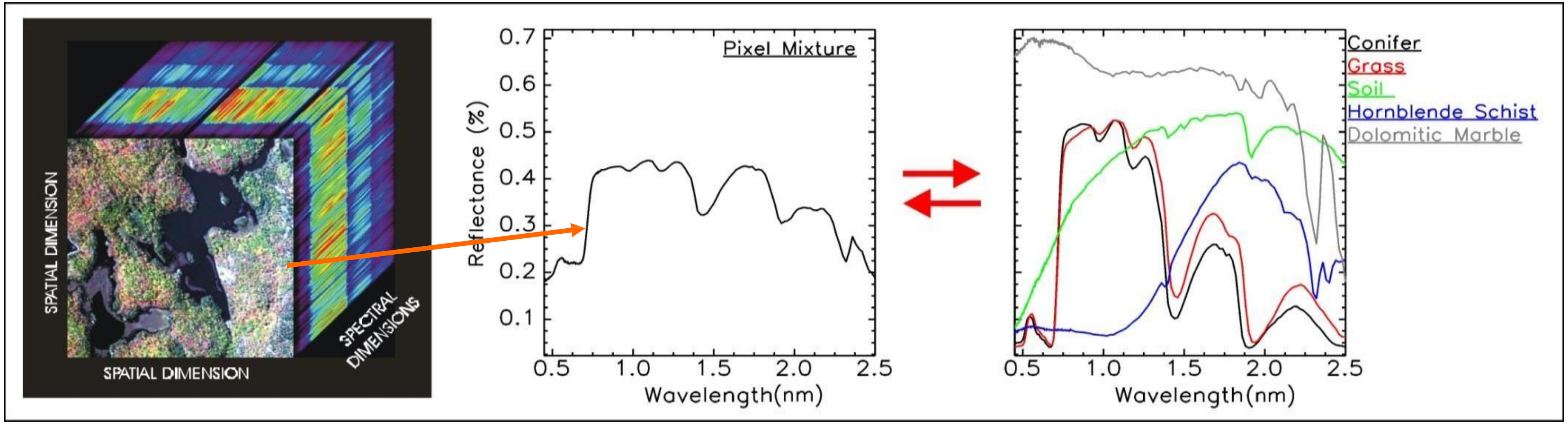


Keshava & Mustard, 2002



8. Endmember analysis of six-band spectra. (a) Reflectance spectra for two substances and shade; (b) image endmembers that tightly bound the variability but cause some spectra to reside the range of acceptable abundance values; (c) reference endmembers that enclose all spectra in a scene.

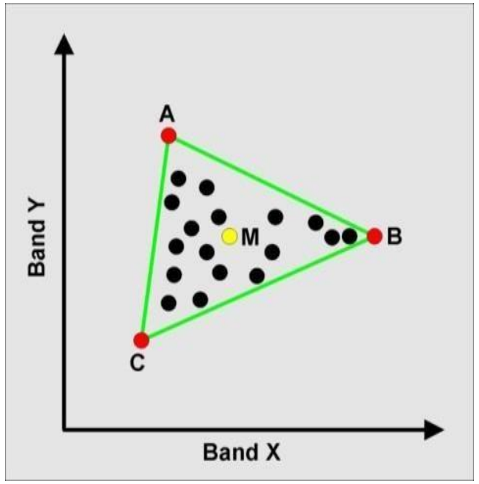
Spectral unmixing: endmembers



- Spectral unmixing can be addressed by decomposing each pixel spectrum into a number of surface constituents (endmembers) and their abundances.

- **Endmembers** are relatively pure materials such as water, healthy vegetation, stressed vegetation, and soil.

- Endmembers are defined spectrally as the vertices of the simplex enveloping the data cloud.



A, B and C are endmembers.

Linear spectral unmixing

$$\rho_b = \sum_{i=1}^{n} F_i \times \rho_{ib} + E_b \quad (1)$$

$$RMS = \sqrt{\left(\frac{\sum_{b=1}^{k} (\rho_b - \rho_b')}{k} \right)^2}$$

$\boldsymbol{\rho_b}$ is the reflectance of the pixel at band ***b***

F_i is the fractional abundance of the endmember ***i***

$\boldsymbol{\rho_{ib}}$ describes the reflectance of endmember ***i*** at band ***b***

b is the band number

i is the endmember number

E_b is the error of the linear fit at band b

$\boldsymbol{k}$ is the number of bands, n is the number of endmembers

RMS Root mean square is the residual between estimated and observed reflectance for a given pixel.

For each band, we can have an equation like Eq. (1). Such that, a linear equation system will be constructed.

Linear spectral unmixing

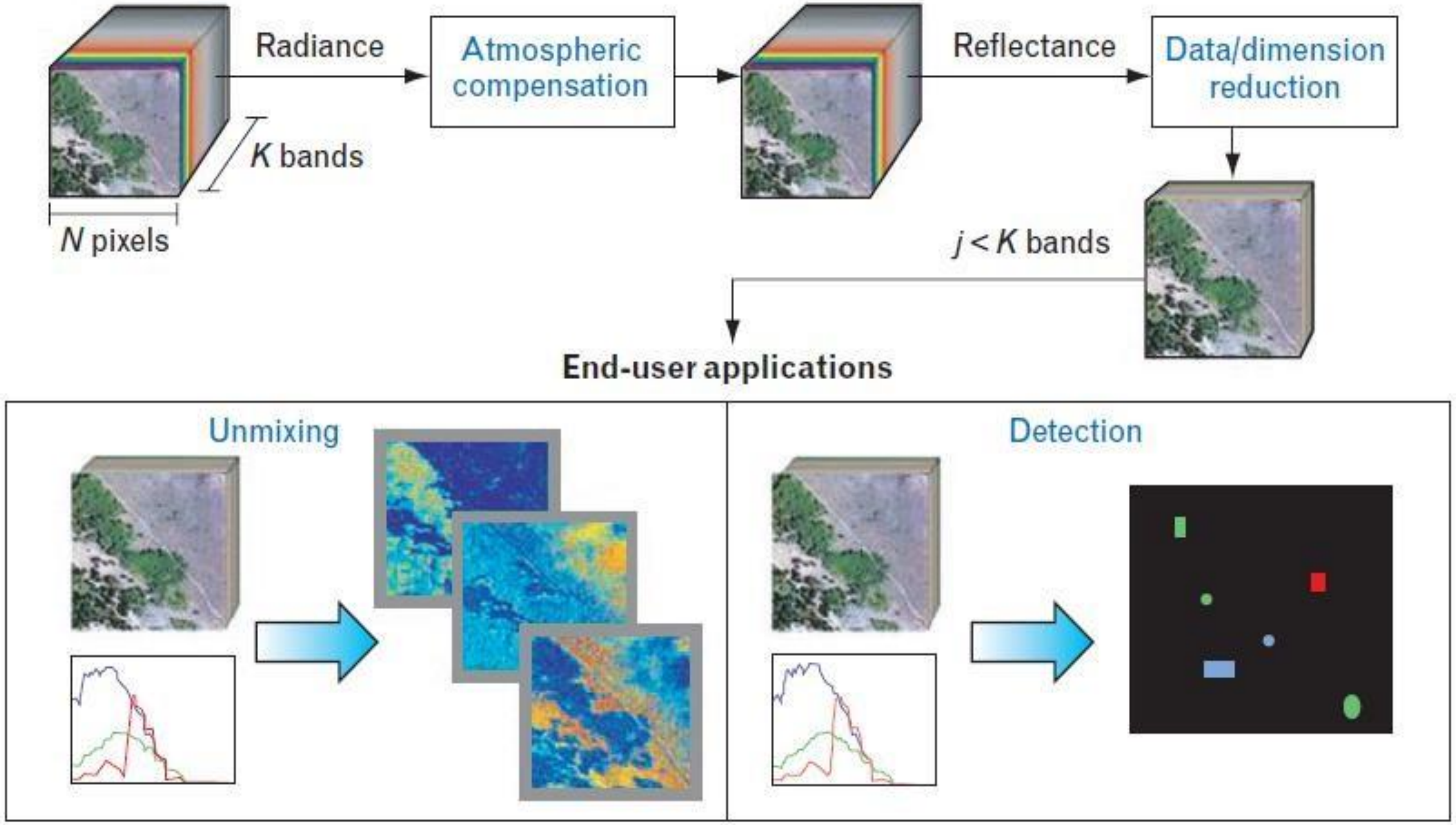
$$\rho_b = \sum_{i=1}^{n} F_i \times \rho_{ib} + E_b \quad (1)$$

$$RMS = \sqrt{\left(\frac{\sum_{b=1}^{k} (\rho_b - \rho_b')}{k} \right)^2}$$

- Linear spectral unmixing involves two steps:
  - Determining endmembers (to derive ρ_{ib})
  - Solving the linear equation system (to derive F_i)

Q3: what factors would affect the endmember variability of UAV images over a rice experimental site?

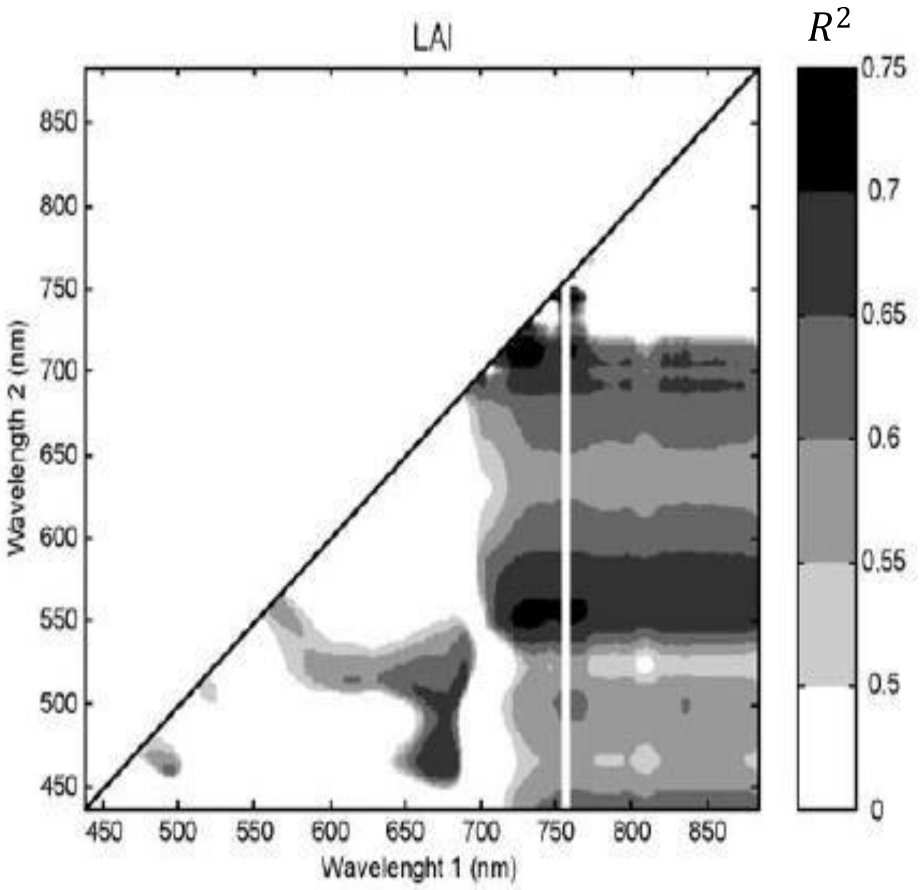
Spectral unmixing for hyperspectral images



An image processing pipeline

Shaw & Burke (2003), LLJ, 1-28.

4. Spectral indices



How to determine λ_1 and λ_2?

- NDVI type:

$$NDVI = \frac{R_{\lambda_1} - R_{\lambda_2}}{R_{\lambda_1} + R_{\lambda_2}}$$

- RVI type:

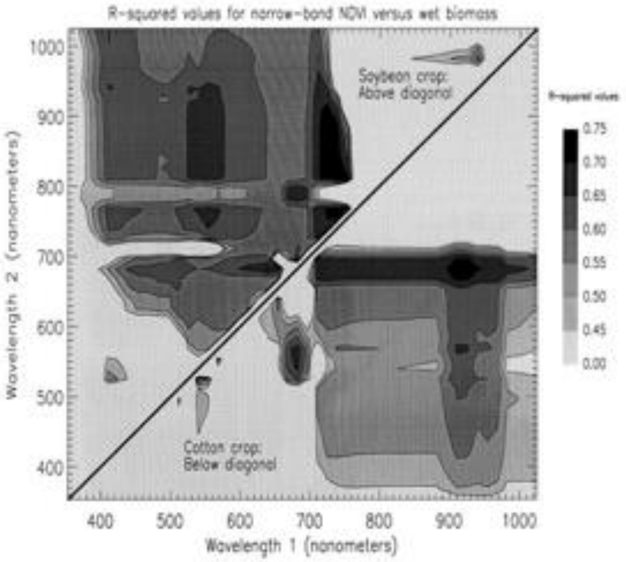
$$\mathrm{R}VI = \frac{R_{\lambda_1}}{R_{\lambda_2}}$$

- From many random two-band combinations, select the optimal spectral index that exhibits the best correlation with the response variable.

Hansen & Schjoerring (2003), RSE

Narrow-band vegetation indices (VIs)

$NDVI = (R\lambda 1 - R\lambda 2) / (R\lambda 1 + R\lambda 2)$



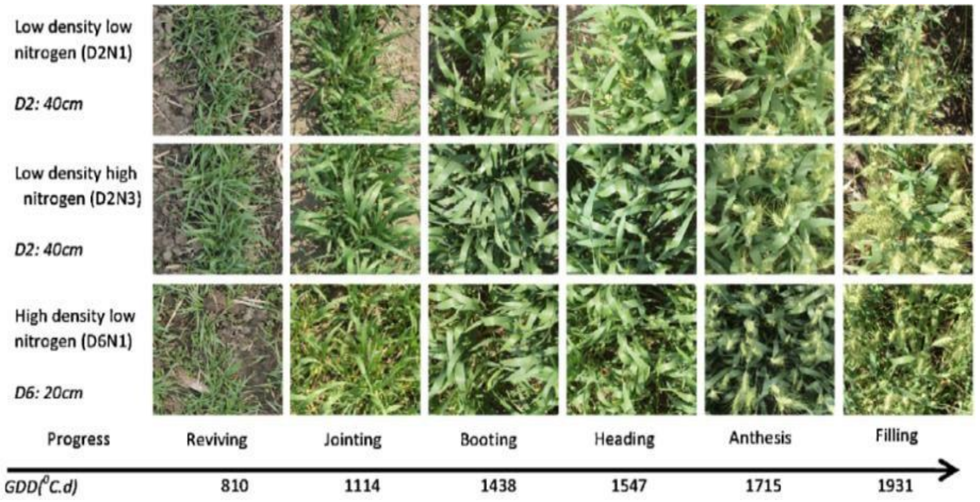
- Thousands of narrow-bands,
- Millions of band combinations
- One of the earliest R^2 contour maps for VI optimization

- Advantages:
  - Sensitive bands or regions are determined for sensor development
  - Empirical models are built for converting spectral measurements to physical values
- Disadvantages:
  - **Distracted** by excessive band combinations
  - Spectral information is not fully used (> 2~3 bands?)

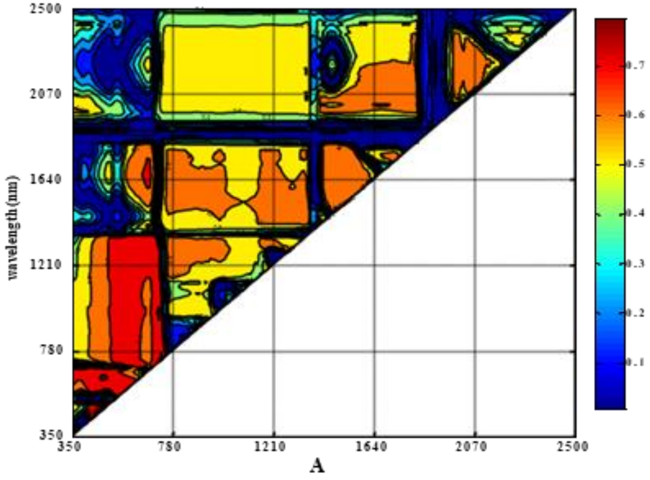
Q4: why do we need narrow-band VIs over existing broad-band VIs?

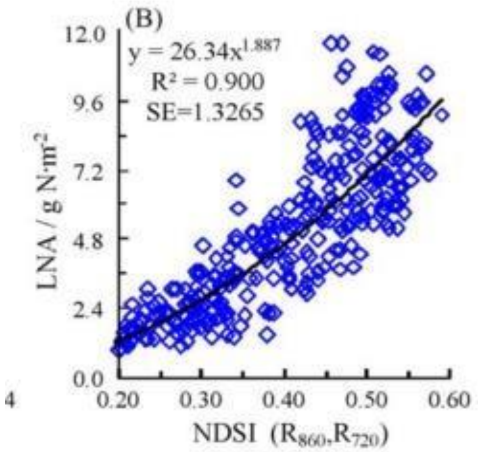
Hyperspectral vegetation indices and their relationships with agricultural crop characteristics
By: Thenkabail, PS; Smith, RB; De Pauw, E
REMOTE SENSING OF ENVIRONMENT Volume: 71 Issue: 2 Pages: 158-182 Published: FEB 2000

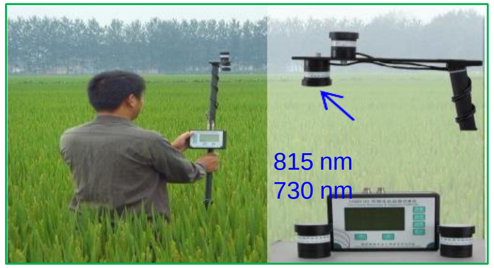
VIs for canopy-level growth monitoring



- Well accepted by agronomists and remote sensing specialists
- The most commonly used approach: Spectral vegetation index (VI)
- Collect VI data with portable multispectral or hyperspectral sensors
- Many VIs have been developed







CGMD 302 (NETCIA)

Spectral data collection

⇩

Band optimization & VI construction

⇩

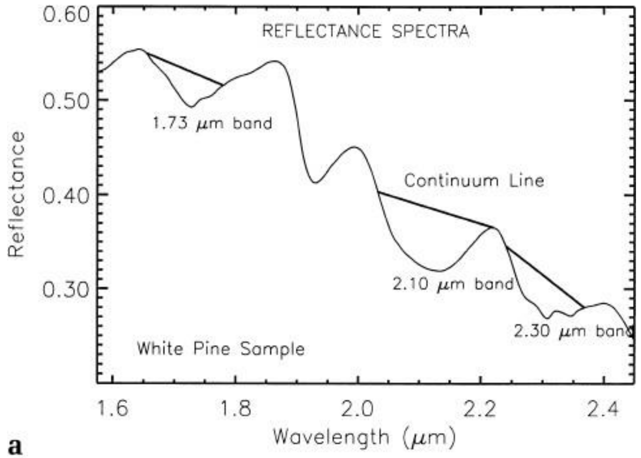
Model establishment

⇩

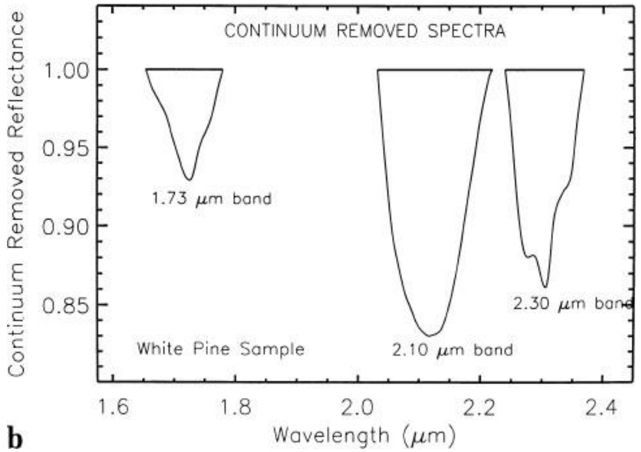
Model application

Yao et al. (2010). *Int. J. Applied Earth Obs. & Geoinfo*. 12, 89-100.

5. Continuum removal analysis



a



b

- Isolation of individual absorption features
- Enhancement of absorption and suppression of background

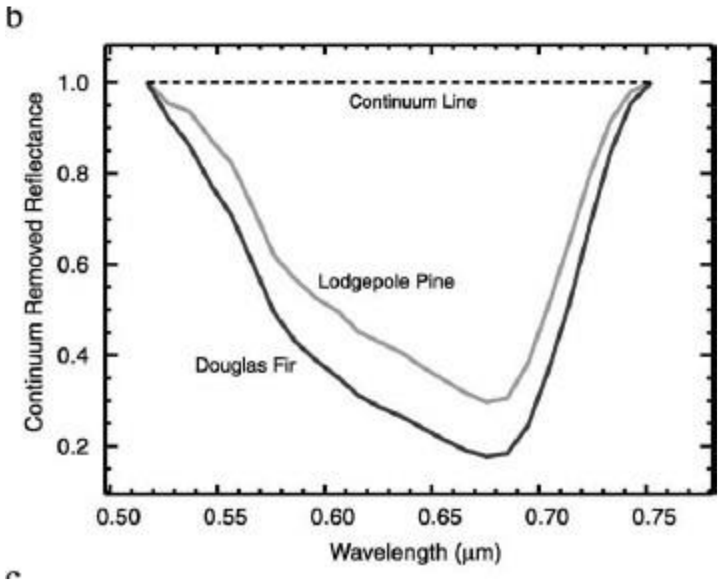
- Determination of continuum endpoints is critical
- Many studies for chlorophyll absorptions, but fewer for N, water, dry matter Constituents
- Absorption features of fresh foliage is not obvious in the SWIR region.

Spectroscopic determination of leaf biochemistry using band-depth analysis of absorption features and stepwise multiple linear regression

By: Kokaly, RF; Clark, RN

REMOTE SENSING OF ENVIRONMENT Volume: 67 Issue: 3 Pages: 267-287 Published: MAR 1999

5. Continuum removal analysis



AVIRIS-derived canopy spectra of two tree species: Lodgepole Pine vs Douglas Fir

Continuum:

Identify the absorption feature of interest

A simple way is to use a linear segment enveloping the absorption feature of interest

- Continuum removal:
  - Dividing the original reflectance spectrum by the corresponding continuum line

$$R_c = \frac{R}{R_c}$$

  - Band depth

$$D = 1 - R_{cr}$$

  - Normalization of band depth

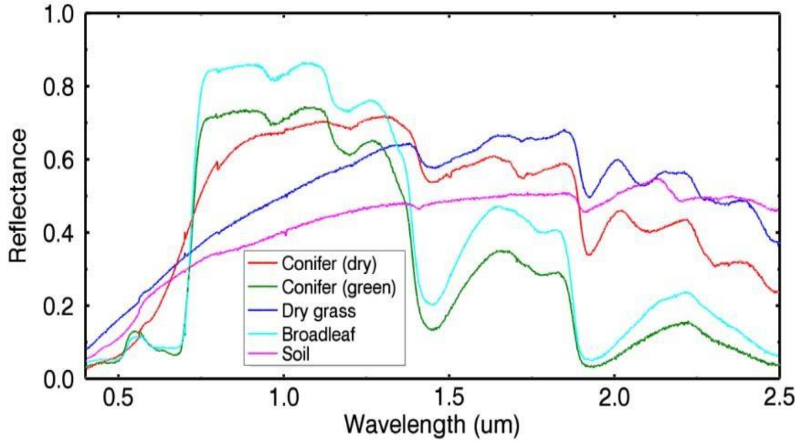
$$D' = \frac{D}{D_c}$$

Band depth at center

Kokaly et al. (2003), RSE

6. Spectral derivative analysis

- Derivatives in spectroscopy:
  - Enhance spectral features of interest
- The first derivative of a reflectance spectra:
  - $\rho'(\lambda_i) = \frac{\rho(\lambda_{i+1}) - \rho(\lambda_i)}{\Delta\lambda}$ (Dawson & Curran, 1998, IJRS)
- Smoothing is needed prior to taking derivatives
- Helps reduce the effect of soil background
- Derivatives are sensitive to noise in spectral data



Q5: why is derivative analysis useful for reducing soil signals in vegetation analysis?

Derivative analysis of hyperspectral data

By: Tsai, F; Philpot, W

REMOTE SENSING OF ENVIRONMENT Volume: 66 Issue: 1 Pages: 41-51 Published: OCT 1998

Times Cited: 340
(from Web of Science Core Collection)

6. Spectral derivative analysis

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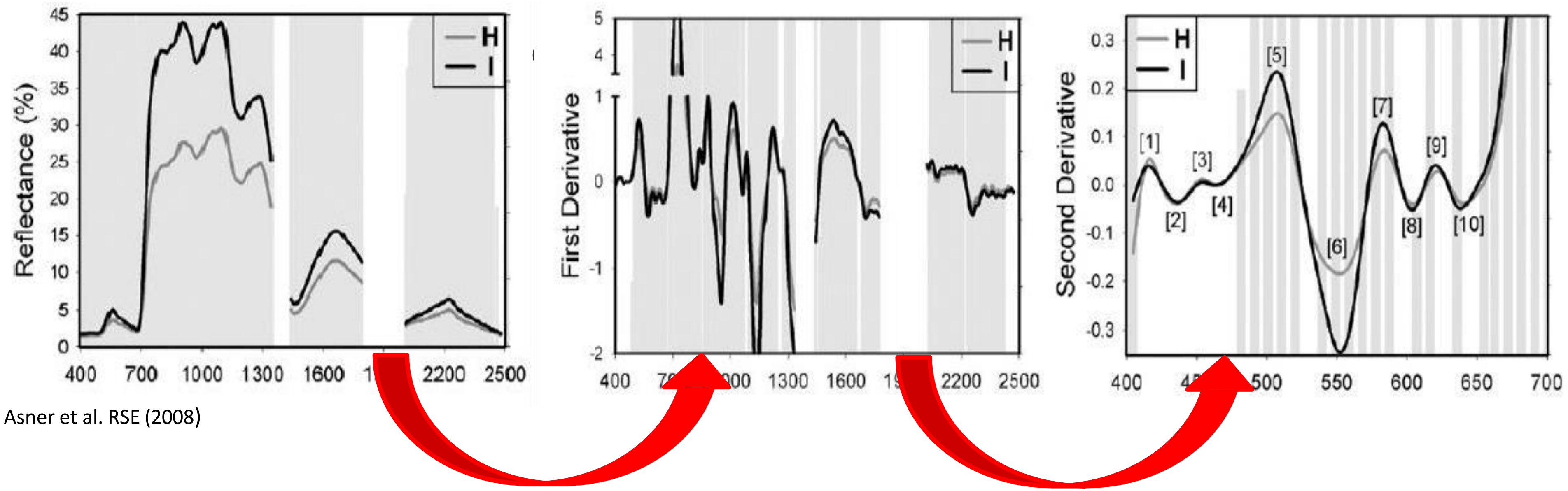
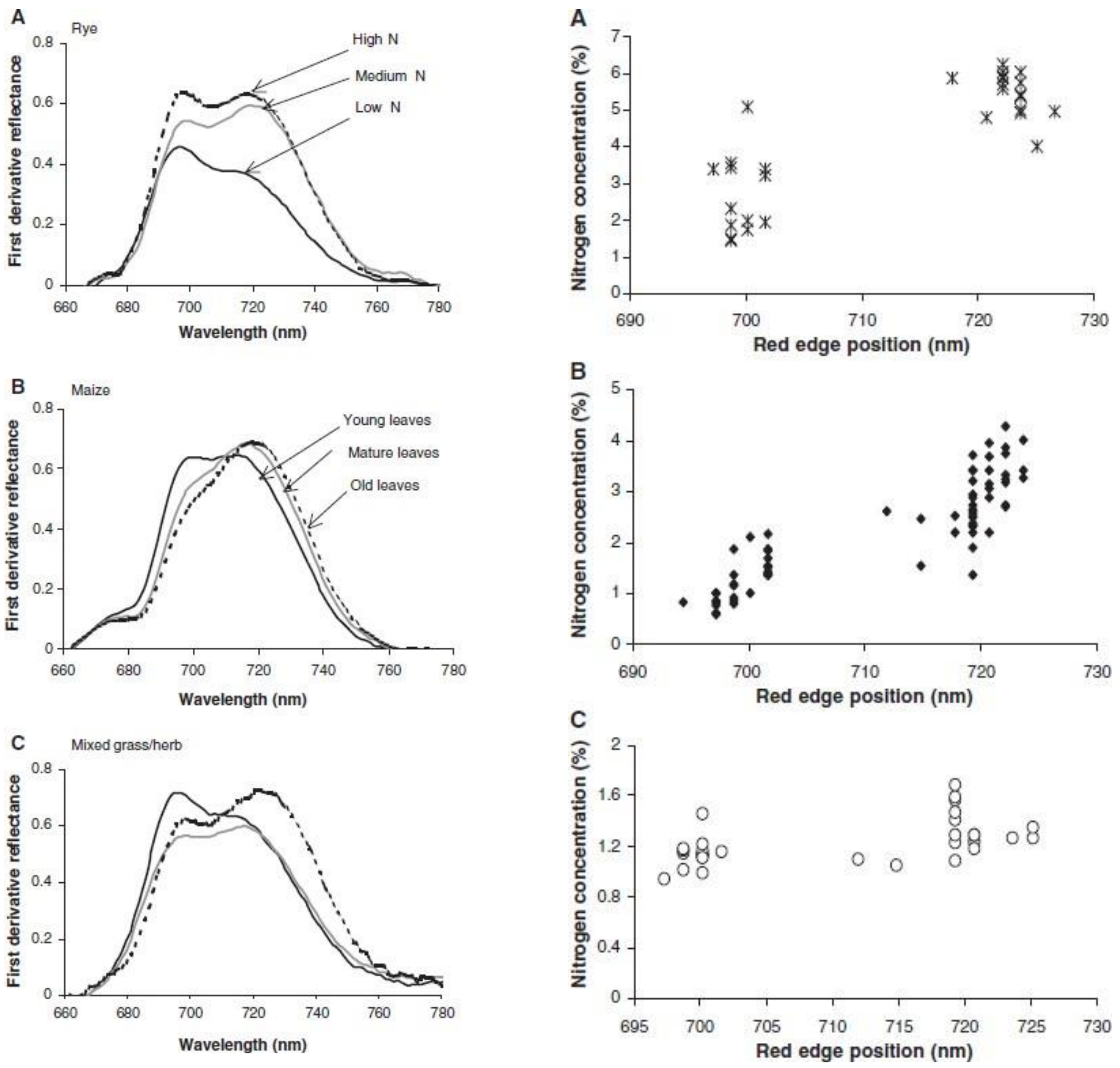


Asner et al. RSE (2008)

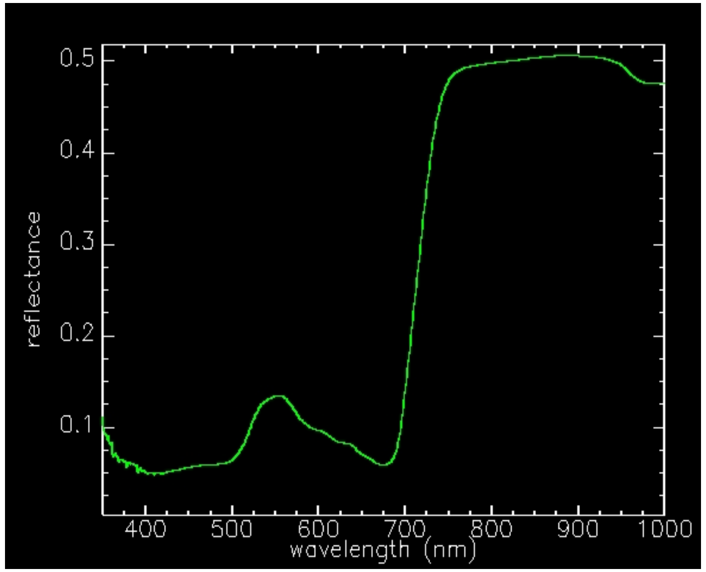
Derivatives for red edge positions

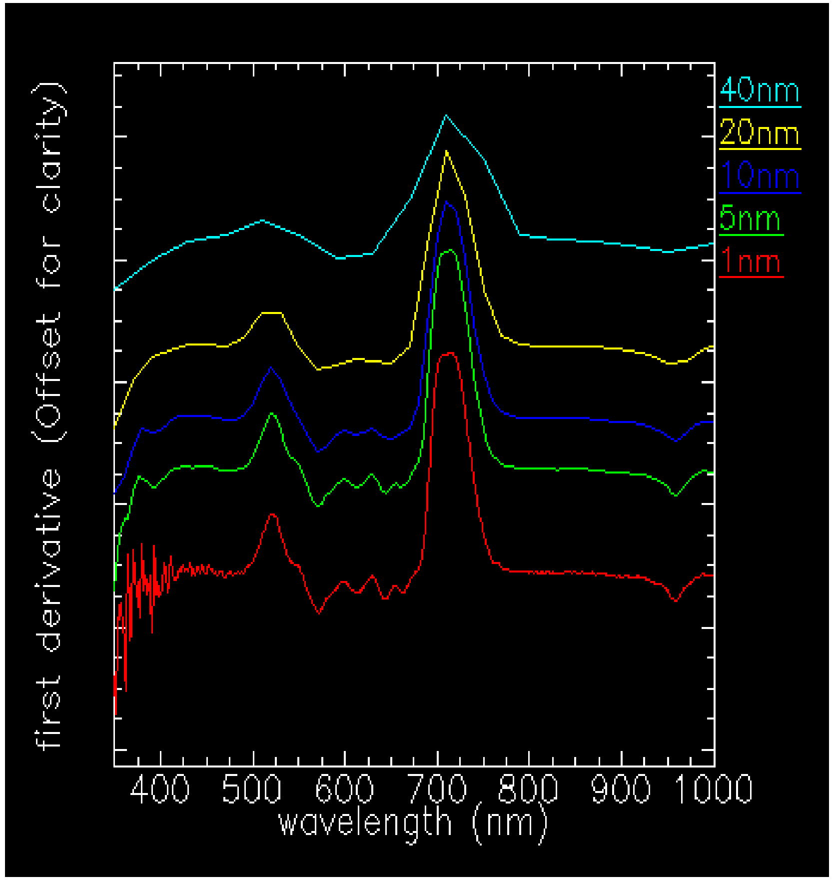


- Red edge position (REP)
  - The wavelength of the max first derivative in the red edge region
  - Double peaks led to discontinuity in REP/N relationship
  - New algorithms are needed to solve the discontinuity problem

(Cho & Skidmore, 2006, RSE, 101, 181-193.)

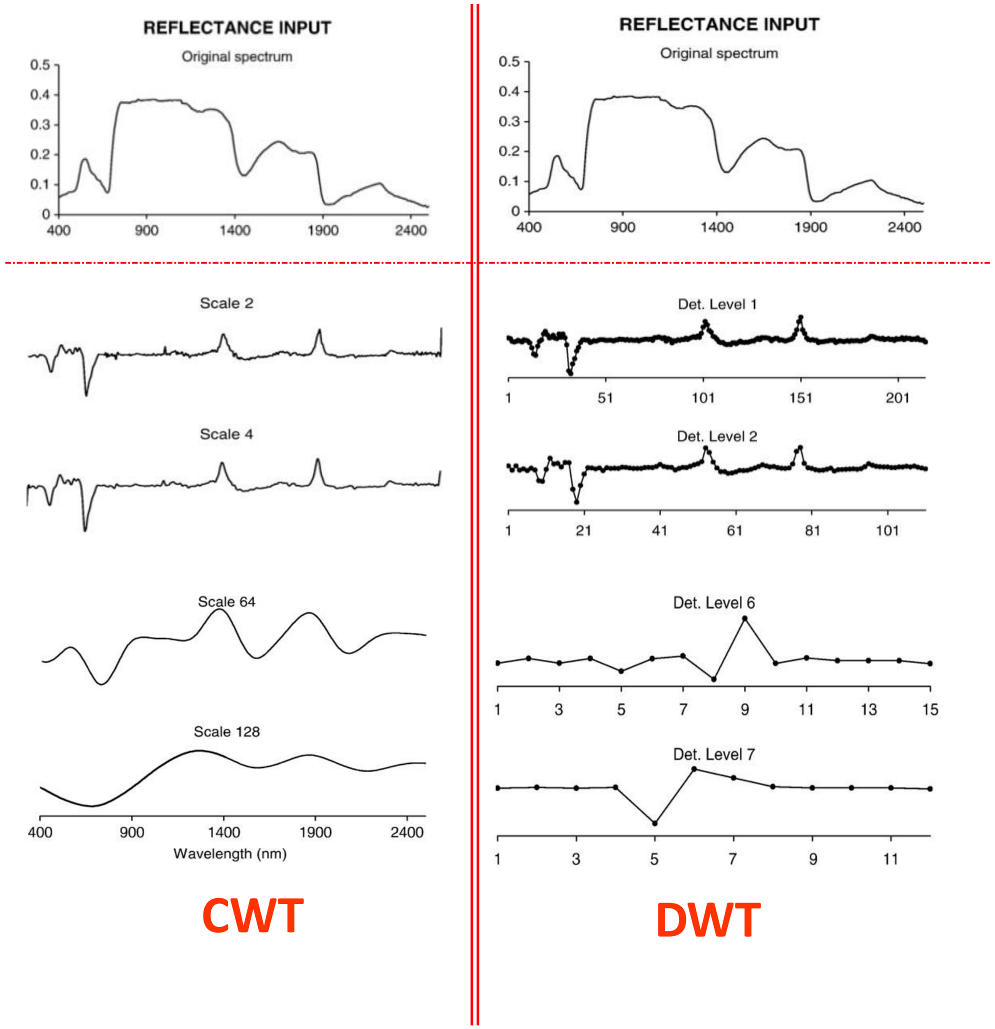
Derivative analysis





- A good smoothing algorithm is required
- Derive spectra become shorter at larger band separations (windows)
- **Multiple windows for multi-scale analysis?**

7. Wavelet analysis

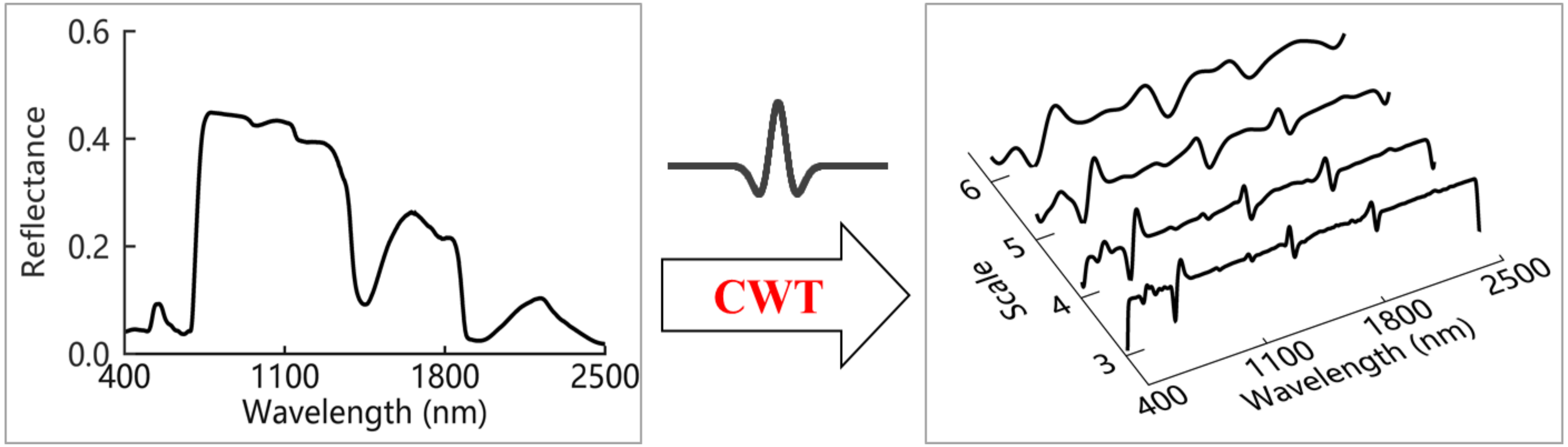


- Discrete (DWT) *vs* continuous (CWT)
- Results of CWT are easier to interpret than those of DWT
- Many vegetation studies using DWT or CWT
- Physical interpretation of CWT results is the key

CWT & DWT of a reflectance spectrum of vegetation, from (Blackburn & Ferwerda, 2008, 112, 1614-1632.)

Continuous wavelet spectral analysis (CWSA)

- CWSA:
  - continuous wavelet analysis of hyperspectral data
  - decompose a reflectance spectrum into a number of scale components for analyzing spectral variation over various scales
  - used for detecting spectral changes



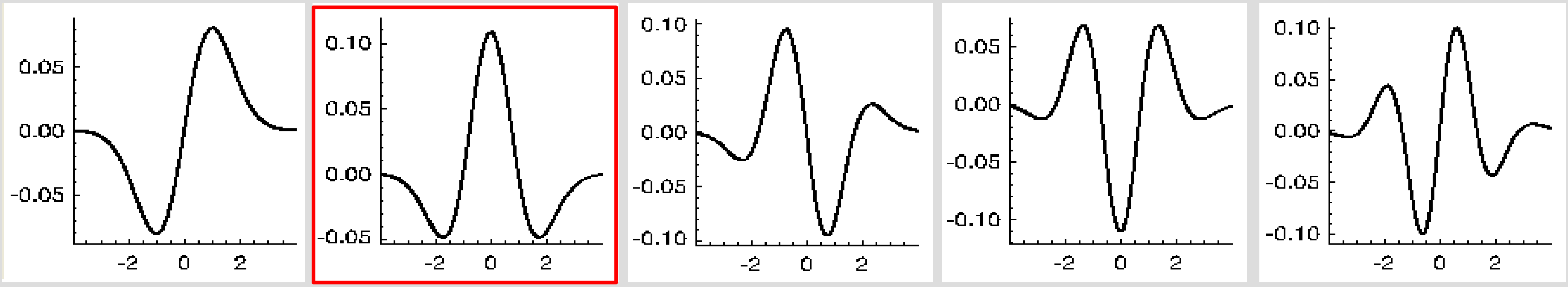
⊗ Convolution

* Correlation

$$W_r(a,b) = r(\lambda)^{\otimes}\psi_a(b) = r(\lambda)^{*}\,\psi_a(-b) = \int_{\lambda 1}^{\lambda 2} r(\lambda)\,\frac{1}{\sqrt{a}}\,\psi\left(\frac{\lambda-b}{a}\right) d\lambda$$

Choice of wavelet function

The Gaussian family: order = 1, 2, 3, 4, 5.

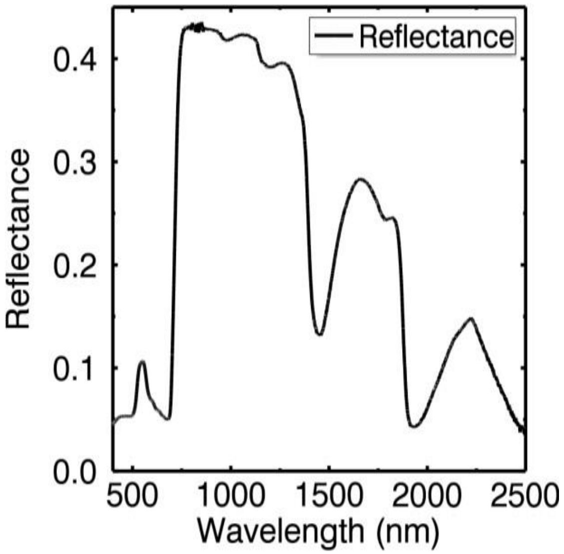


- Convolution with a DoG2 =
  - 1. convolution with a Gaussian function
  - 2. taking the 2nd derivative

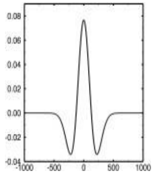
$$W_r\ (a,b) = r(\lambda) * \psi_a(-b)$$

- Using DoG2 as the wavelet function:
  - To avoid taking another smoothing procedure
  - To match absorption features in vegetation reflectance spectra

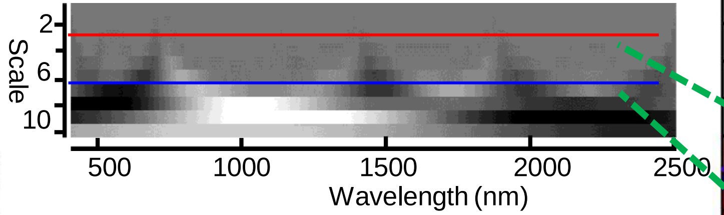
Continuous wavelet transform (CWT)

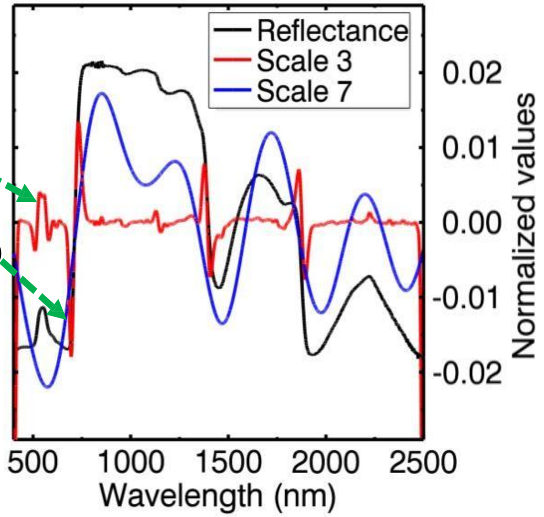


CWT



Wavelet power scalogram





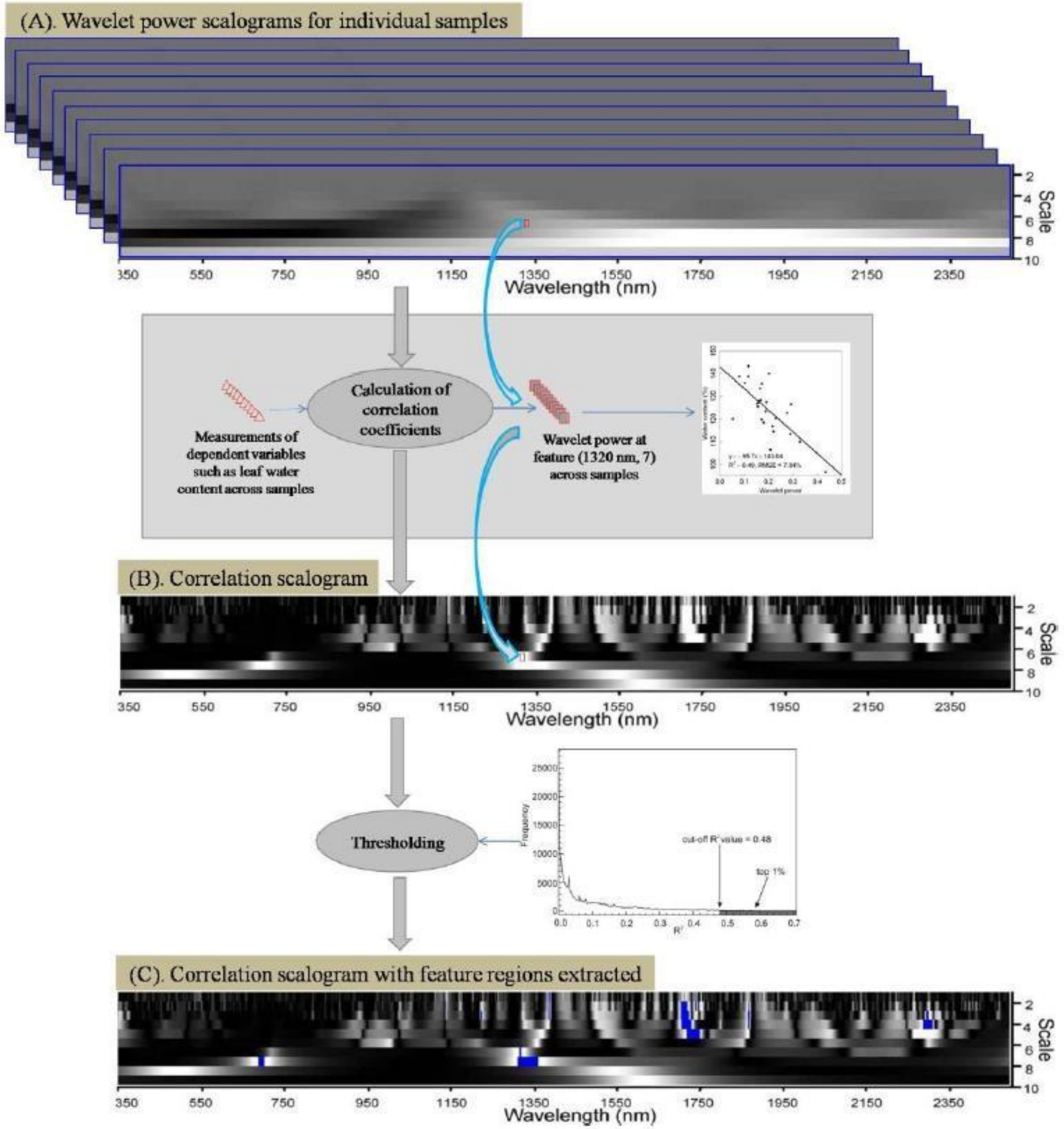
Reflectance domain

Wavelet domain

- Band by *wavelength*
- Reflectance:
  - Spectral value at a band (>0)

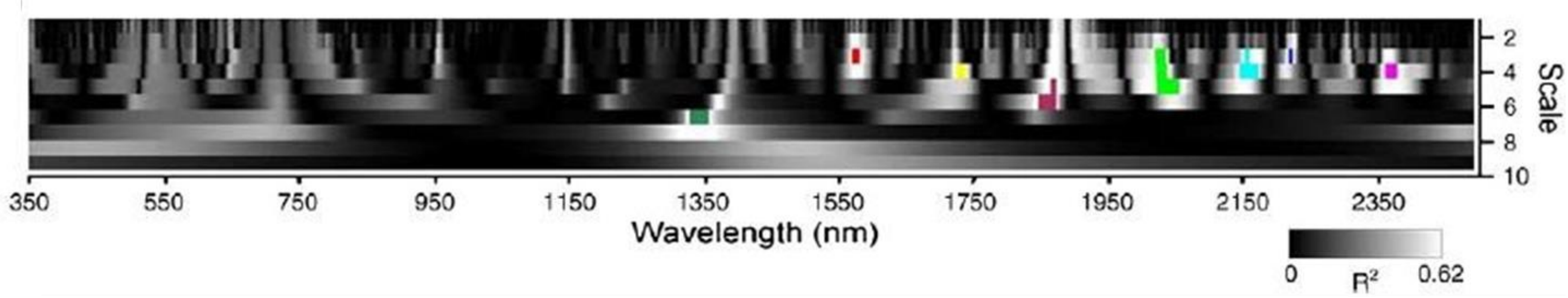
- Wavelet feature by *wavelength* and *scale*
  - Also called *wavelet coefficient*
- Wavelet power:
  - Spectral value at a wavelet feature (<0, =0, or >0)
  - Similarity of a spectral segment to a wavelet
- Scale
  - Low scale: detail (absorption features and noise)
  - High scale: overall pattern (continuum or baseline)

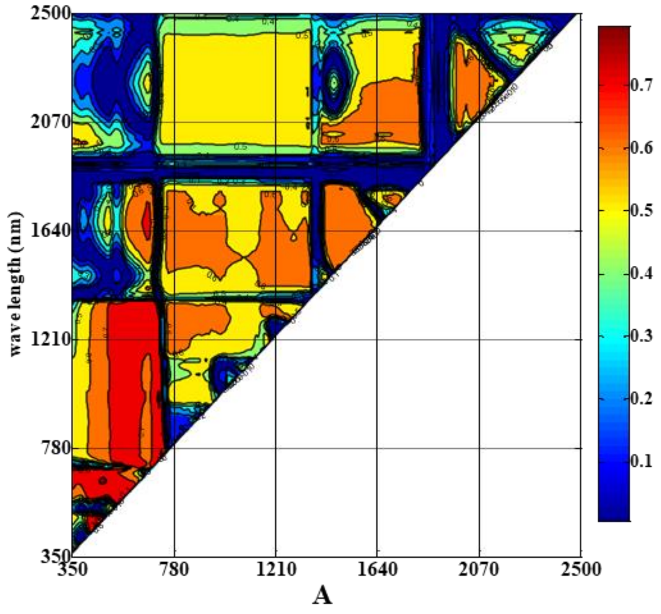
Workflow of the CWSA methodology



Cheng et al., (2010)

Wavelet features vs. spectral indices





(Yao et al., 2010)

- Extraction of optimal wavelet features is similar to that of spectral indices

Q6: how to use wavelet features?

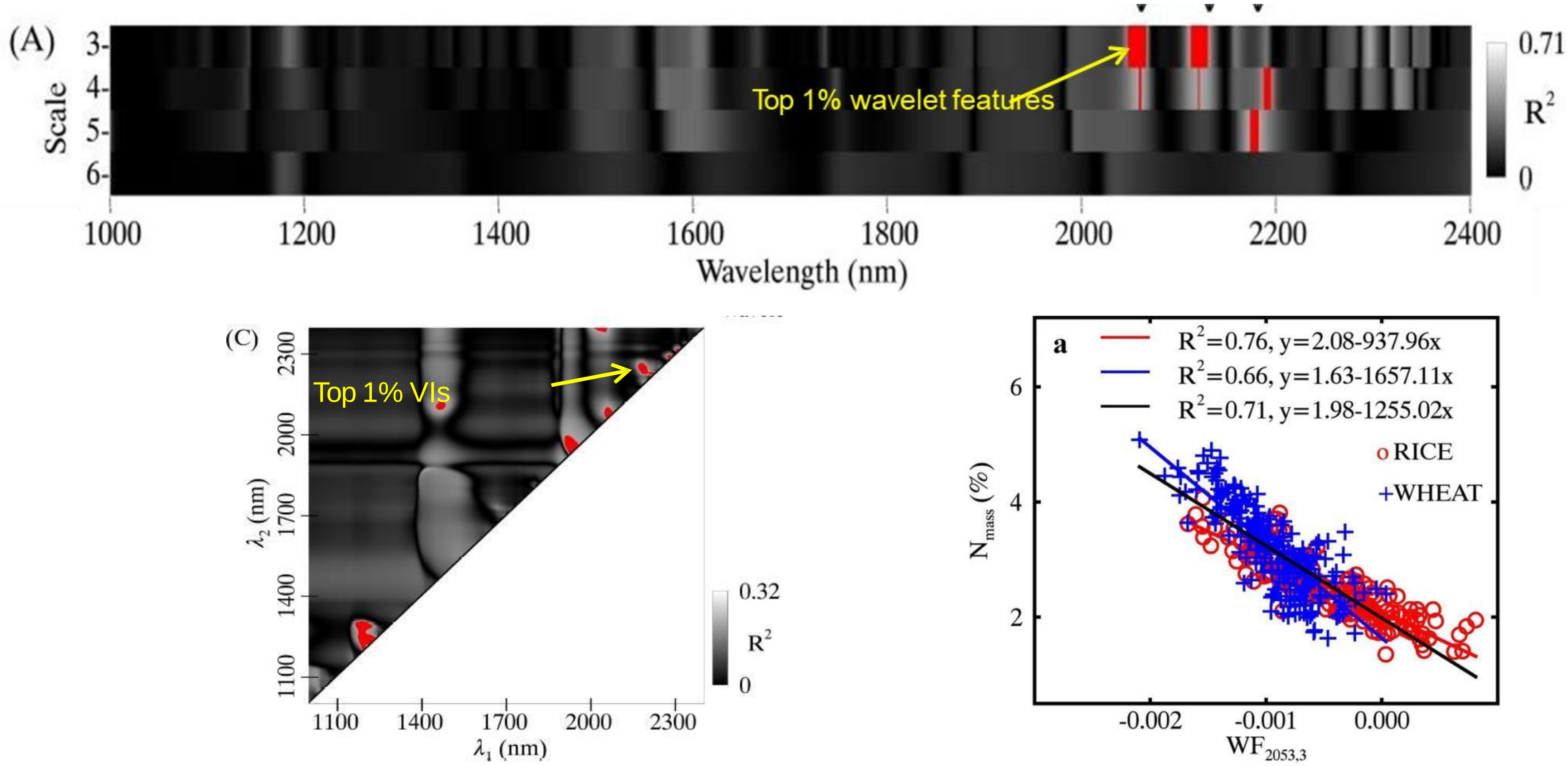
Spectroscopic determination of leaf water content using continuous wavelet analysis

By: Cheng, T.; Rivard, B.; Sanchez-Azofeifa, A.

REMOTE SENSING OF ENVIRONMENT Volume: 115 Issue: 2 Pages: 659-670 Published: FEB 15 2011

Times Cited: 115
(from Web of Science Core Collection)

Wavelet features vs. spectral indices



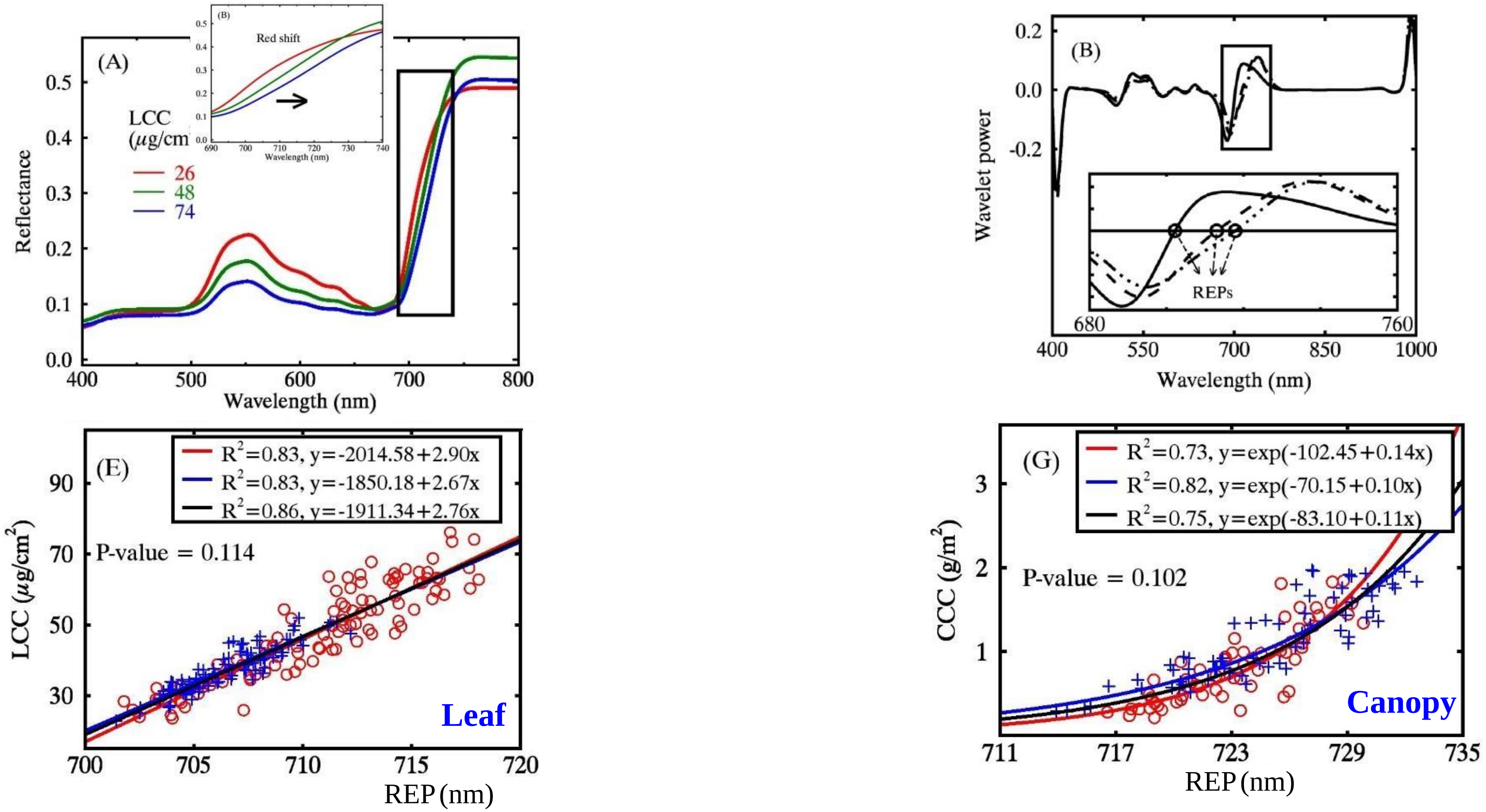
- The top 1% wavelet features are less scattered than VIs, with better correspondence to N absorption features
- Based on SWIR bands, wavelet features outperformed VIs for N mass estimation

Li et al. (2018). Plant Methods. 14: 76

Wavelet-based red edge position (WREP)

- **WREP**: a new algorithm to extract red edge position based on wavelet transformed spectra

<u>*Principle:*</u> *wavelet transform (2^{nd} DoG) -> zero-crossing point -> maximum first derivative -> REP*



Li et al., (2017). *ISPRS Journal of Photogrammetry and Remote Sensing, 129*, 103-117.

Discussion

- Which technique to use?
  - Purpose
  - Experience
  - Understanding

Further reading

- **USGS Spectroscopy Lab**
  - http://speclab.cr.usgs.gov/index.html

- DIP textbook Chapter 11

- References:

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  - Hansen & Schjoerring. (2003), Remote Sensing of Environment, vol. 86, 542-553.
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