Remotely sensed fuel moisture using leaf and imaging spectroscopy

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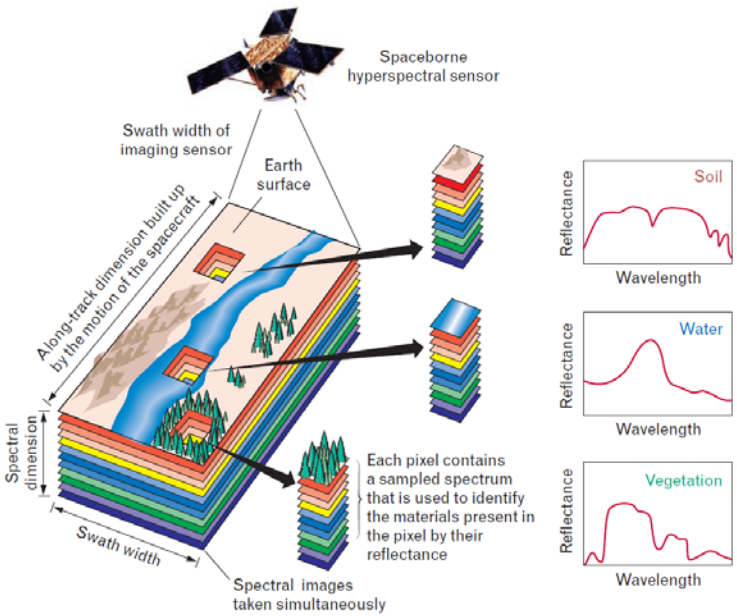
Spectroscopy

- **Imaging spectroscopy**
  - Also called hyperspectral imaging, hyperspectral remote sensing
  - "a new tool that can be used to map specific materials by detecting specific chemical bonds." (http://speclab.cr.usgs.gov)



(Shaw & Burke, 2003)

- **Leaf spectroscopy**
  - Used in field or laboratory
  - Understand the physical mechanism of estimating FMC using spectroscopy data

(Courtesy of ASD Inc.)

- Advantages of using spectroscopy data
  - Determination of the most sensitive spectral regions for specific mapping tasks
  - Analysis of specific absorption features

Remote sensing of fuel moisture content

FMC is a leaf mass based variable:

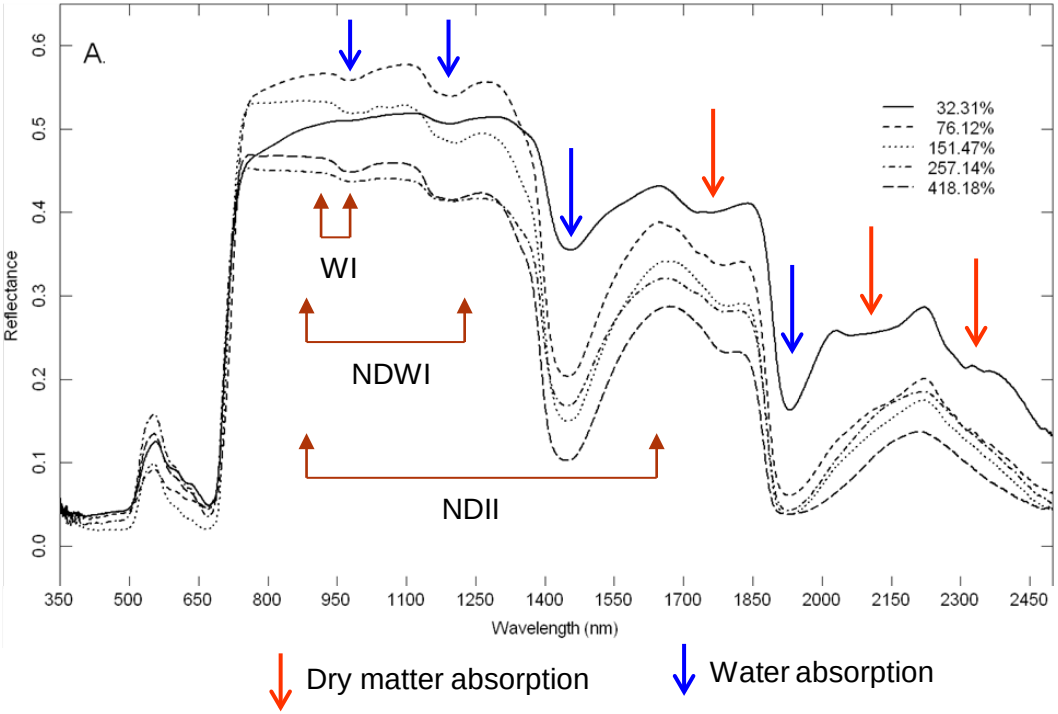
$$FMC = \frac{FW - DW}{DW}$$

FMC is related to two leaf area based variables equivalent water thickness (EWT) and dry matter content (DMC):

$$FMC = \frac{EWT}{DMC}$$

$$EWT = \frac{FW - DW}{A}$$

$$DMC = \frac{DW}{A}$$



- What are the spectral changes related to FMC variation?
  - Overall amplitude due to strong water absorption in the entire SWIR region
  - Overlapping absorption features of dry matter (lignin, cellulose, nitrogen, etc.)
- Both water and dry matter absorptions vary with FMC. Can we just use water indices (WI, NDWI, NDII) to estimate FMC?

A summary of studies on the spectroscopic estimation of leaf FMC

- Methods:
  - Spectral indices
  - Inversion of radiative transfer models (PROSPECT)
  - Partial least squares (PLS) regression
  - Genetic-algorithm partial least squares (GA-PLS) regression
  - Continuous wavelet analysis

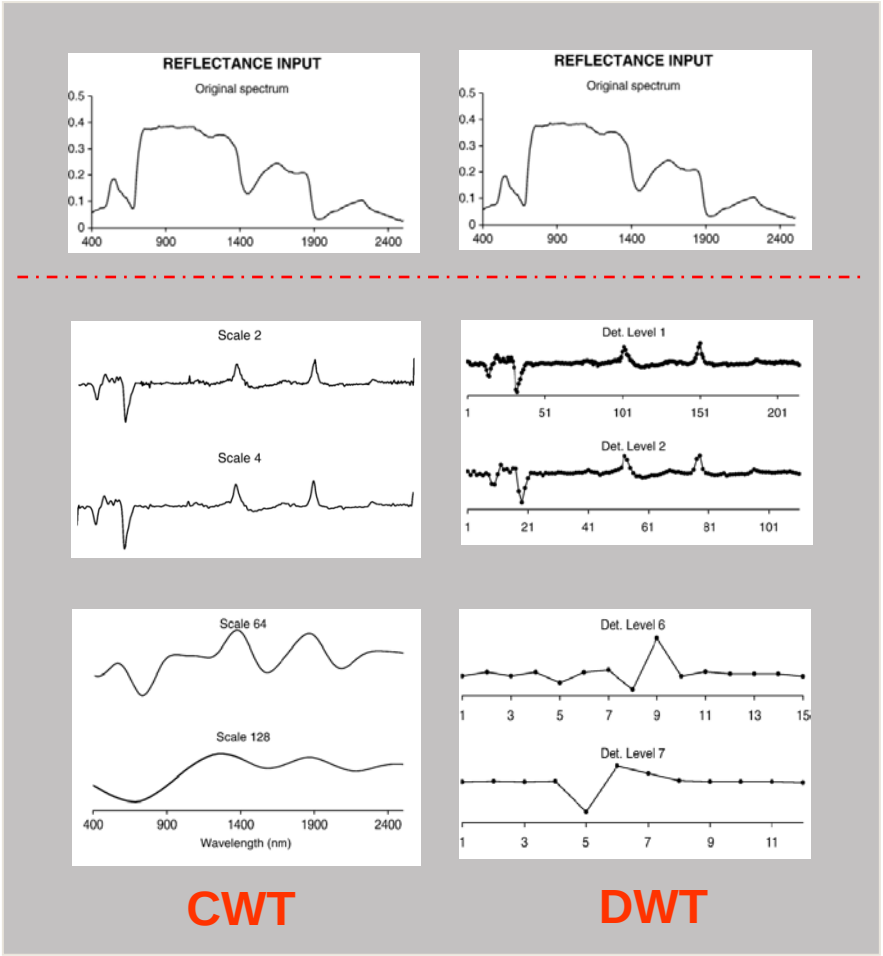
Reference	Species	Spectral range (nm)	Method	Related to	Best accuracy
Curran et al. (1992)	*Amaranthus tricolor*	400–2400	First derivative spectra	LWC_D (22.31–91.43%)	$R^2 = 0.45$, RMSE = 15.9%
Peñuelas et al. (1997)	5 species (from field)	390–1100	Spectral index WI	LWC_D	$R^2 = 0.31$
	8 species (potted seedlings)			LWC_D	$R^2 = 0.49$
Dawson et al. (1998)	*Pinus elliottii*	400–2500	Artificial Netural Network	LWC_D (52–63%)	$R^2 = 0.86$, RMSE = 1.3%
Datt (1999)	21 *Eucalyptus* species	400–2500	Spectral indices MSI, WI, $(R_{850} - R_{2218})/(R_{850} - R_{1928})$; $(R_{850} - R_{1788})/(R_{850} - R_{1928})$; NDWI and TM5/TM7	EWT (0.009–0.025 g/cm^2)	$R^2 = 0.61$
				LWC_F (40.8–71.7%)	Not significant
				LWC_D (70.4–221.5%)	Not significant
Tian et al. (2001)	Winter wheat	350–2500	CR over 1650–1850 nm	LWC_F (39.62–80.12%)	$R^2 = 0.87$
Pu et al. (2003)	*Quercus agrifolia*	350–2500	CR centered at 975 nm, 1200 nm and 1750 nm; three-band ratio indices derived at 975 nm and 1200 nm	LWC_F (0.45–57.94%)	$R^2 = 0.86$
Maki et al. (2004)	*Nerium oleander var. indicum, Liriodendron tulipifera, Betula platyphylla*	400–2400	Spectral index: NDWI	EWT (0.002–0.138 g/cm^2)	$R^2 = 0.62$
				LWC_D (33.33–285.71%)	$R^2 = 0.08$
Danson and Bowyer (2004)	subset of LOPEX	400–2500	Spectral indices MSI, WI, NDWI, TM5/TM7 and GVMI	EWT (0.0003–0.0655 g/cm^2)	$R^2 = 0.88$, N.L.
	Simulations with PROSPECT model	400–2500		LWC_D (9–1258%)	$R^2 = 0.54$
				EWT (0.0425 ± 0.0142 g/cm^2)	$R^2 = 0.88$
				LWC_D (184 ± 101%)	$R^2 = 0.78$
Riaño et al. (2005)	37 species from LOPEX	400–2500	PROSPECT model inversion	EWT	$R^2 = 0.94$
				LWC_D	$R^2 = 0.33$
Stimson et al. (2005)	*Pinus edulis*	350–2300	CR based absorption indices at 970 nm and 1200 nm; red edge; spectral indices NDWI and NDVI	LWC_D (approx. 30–60%)	$R^2 = 0.71$
	Juniperus monosperma			LWC_D (approx. 35–45%)	$R^2 = 0.50$
Li et al. (2007)	37 species from LOPEX	400–2500	Genetic Algorithm Partial Least Squares (GA-PLS)	EWT	$R^2 = 0.94$, RMSE = 0.0017 g/cm^2
				LWC_D	$R^2 = 0.89$, RMSE = 68.5%
Colombo et al. (2008)	Poplar trees	350–1800	Spectral indices WI, NDWI, SRWI, NDII, MSI, SR, $(R_{895} - R_{675})/(R_{895} + R_{675})$	EWT (0.0091–0.0154 g/cm^2)	$R^2 = 0.52$
				LWC_D (110.65–217.64%)	$R^2 = 0.25$
			PROSPECT model inversion	EWT (0.0091–0.0154g/cm^2)	$R^2 = 0.65$
				LWC_D (110.65–217.64%)	$R^2 = 0.00$
Asner and Martin (2008)	162 tropical forest species	400–2500	PLS regression	LWC_F (43–79%)	$R^2 = 0.69$, RMSE = 4%

(Cheng et al., 2011)

- Estimations are good for EWT but not good enough for FMC
  - Water indices (designed for EWT), particularly for multiple species
  - PROSPECT model inversion (hard to invert dry matter content)

Wavelet transform

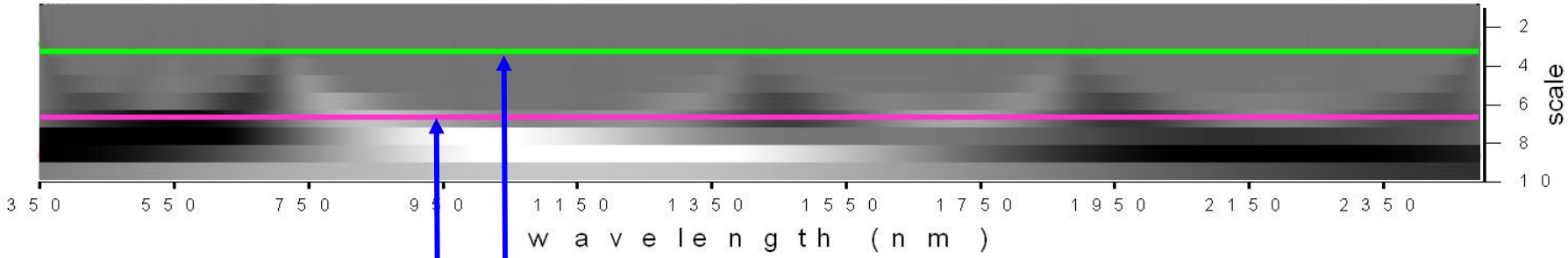
- Allows for analysis of signals at various scales
- Converts a reflectance spectrum into a set of coefficients (wavelet features)
- *Discrete* (DWT) vs *Continuous* (CWT)
- Most vegetation studies use DWT, but the results are difficult to interpret
- CWT
  - Multi-scale decomposition
  - Emphasize spectral regions rather than individual bands
  - Takes advantage of continuous nature of spectroscopy data

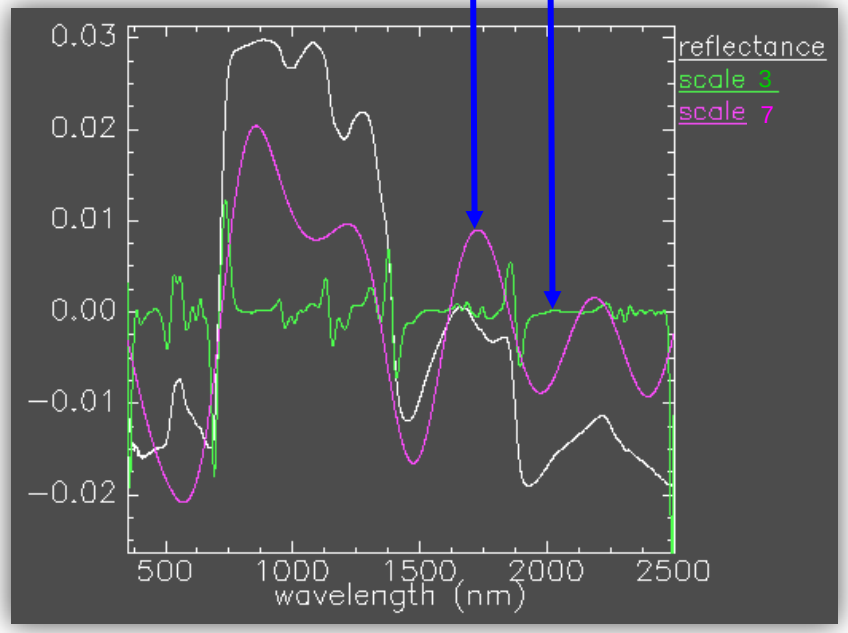


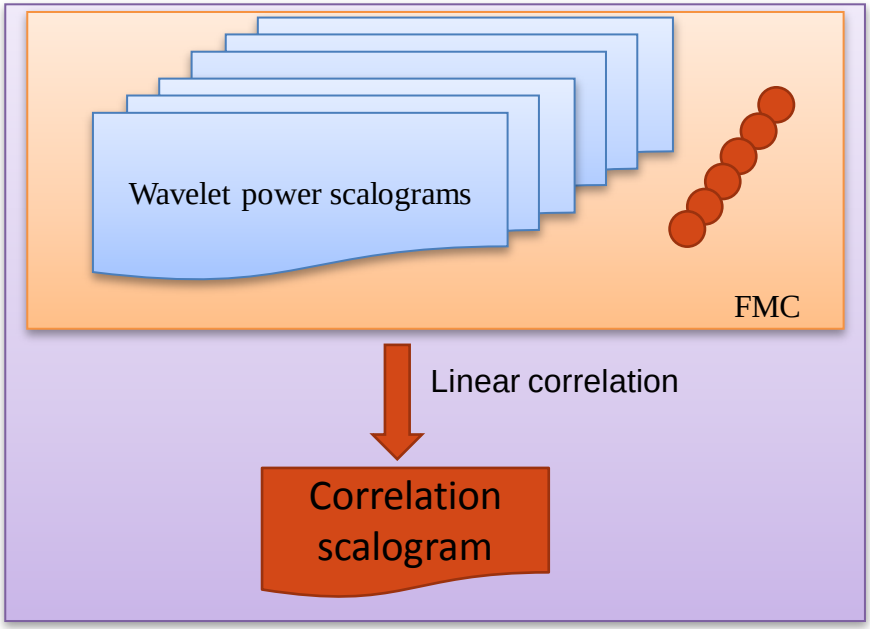
CWT & DWT of a leaf reflectance spectrum
(Blackburn & Ferwerda, 2008)

Continuous wavelet analysis (CWA)

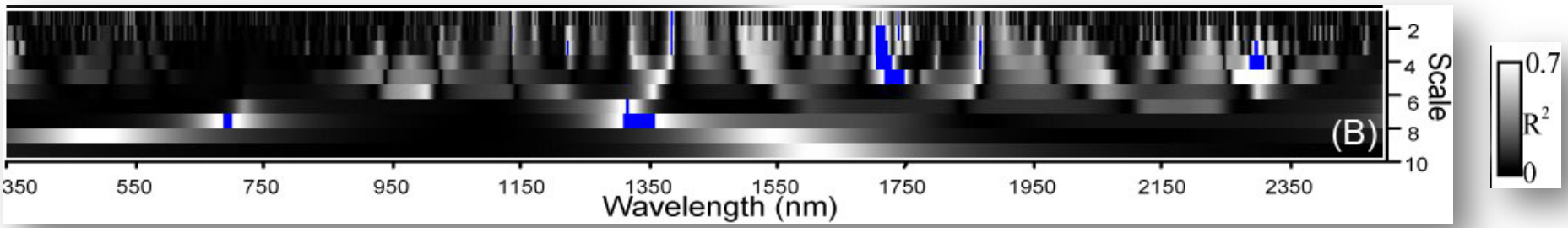
CWT output of a reflectance spectrum (wavelet power scalogram)



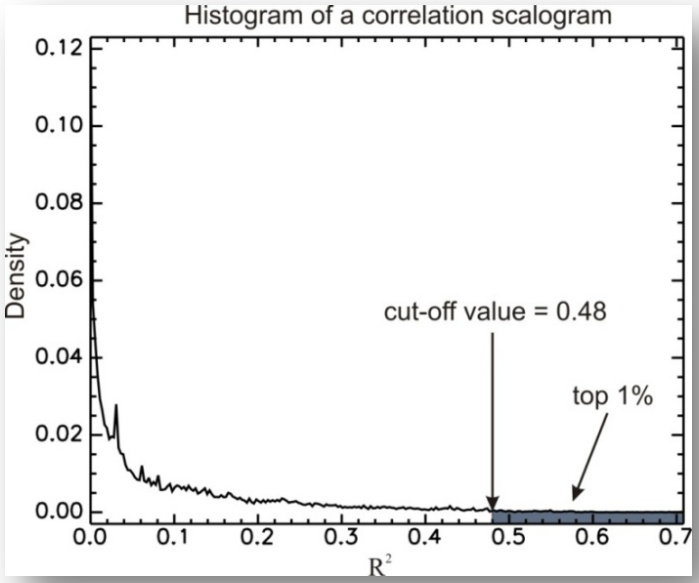




Correlation scalogram



Blue areas represent the top 1% correlations with FMC.



Histogram of the correlation scalogram above.

- The correlation scalogram demonstrates the magnitude of linear correlation (R^2) between wavelet coefficients and leaf FMC across all samples.
- By applying a threshold (1%) to the R^2 scalogram, the features producing the highest correlations to leaf FMC are highlighted.

Cheng, T., Rivard, B., Sánchez-Azofeifa, G. A., Feng, J. & Calvo-Polanco, M. (2010). Continuous wavelet analysis for the detection of green attack damage due to mountain pine beetle infestation. *Remote Sensing of Environment, 114*, 899-910.

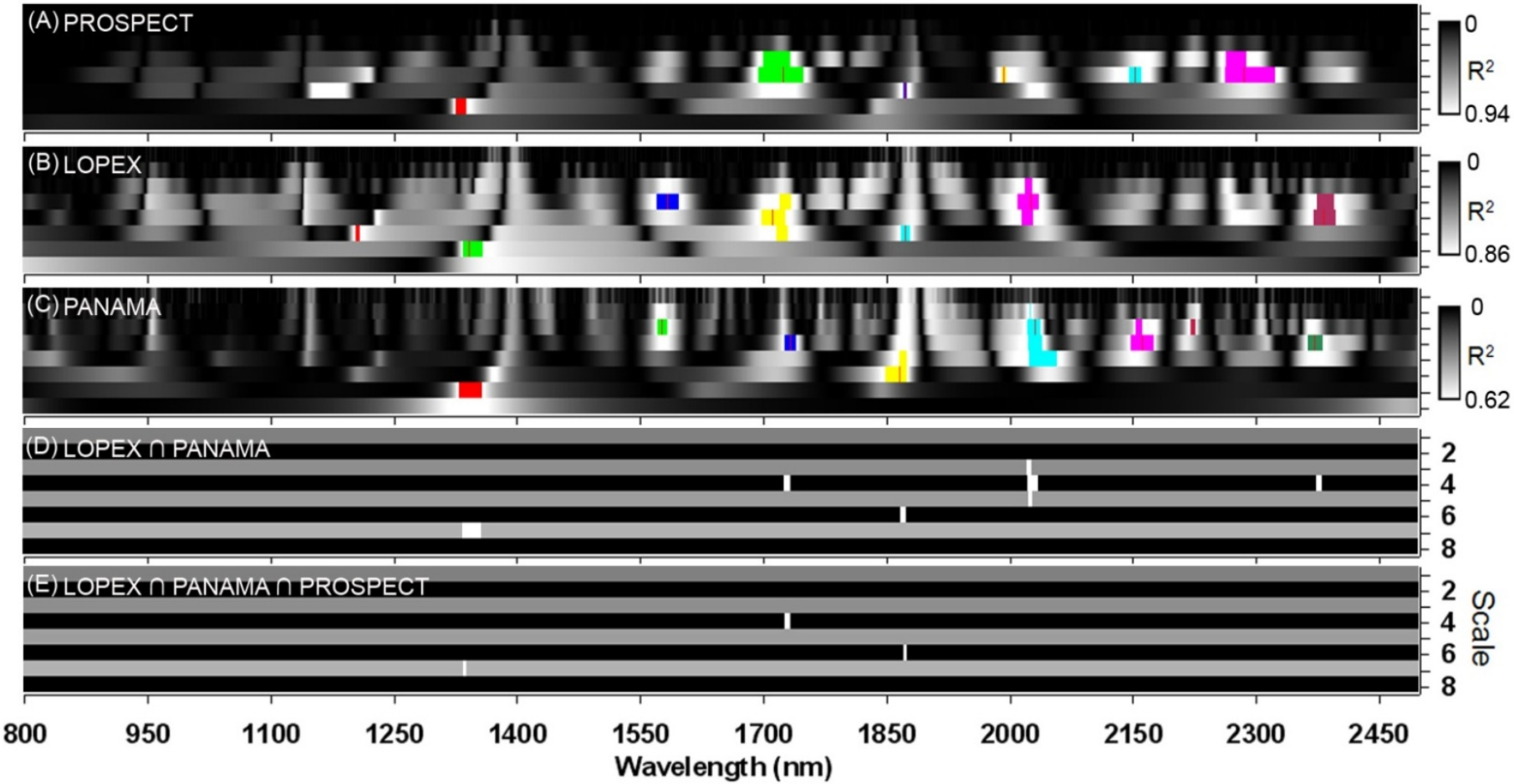
A leaf-level study for multiple species

Data set	Sample size	Mean ± s.d.	Min	Max	# of species	Origin
LOPEX	325	240.47±193.18	9.43	1258.57	45	Broadleaf trees and crops in Ispra, Italy
PANAMA	265	143.60± 52.44	32.31	418.20	47	Trees and lianas in tropical forests of Panama
PROSPECT	2495	177.14±107.22	36.51	1154.36	-	Simulated using PROSPECT-5 (Féret et al., 2011)

- Data sets contain leaf FMC and reflectance (400-2500 nm with 1 nm step) data
- Simulated data
  - Parameters estimated from a global leaf database
  - Represent leaves from various species and growing conditions
- 60% of samples for calibration and 40% for validation
- Goals:
  - To evaluate CWA for estimating leaf FMC across a large collection of plant species
  - To determine robust wavelet features for FMC estimation

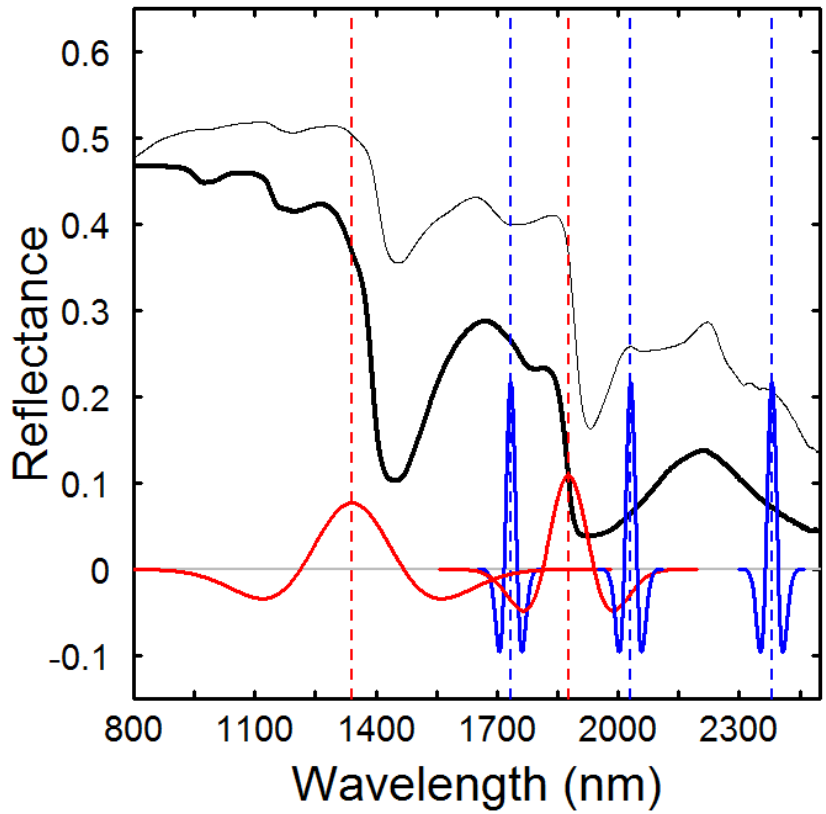
Cheng, T., Rivard, B., Sánchez-Azofeifa, G. A., Féret, J. B., Jacquemoud, S. & Ustin, S. L. (2012). Predicting leaf gravimetric water content from foliar reflectance across a range of plant species using continuous wavelet analysis. *Journal of Plant Physiology*, *169*, 1134-1142.

Cheng, T., Rivard, B., & Sánchez-Azofeifa, G. A. (2011). Spectroscopic determination of leaf water content using continuous wavelet analysis. *Remote Sensing of Environment, 115,* 659-670.



- Almost all feature regions occurred in the SWIR region (1300-2500 nm)
- Consistent feature regions were found across data sets
  - Five were common to the two measured ones (absorptions by water, cellulose and lignin, nitrogen)
  - Three were common to all data sets (water, cellulose and lignin)

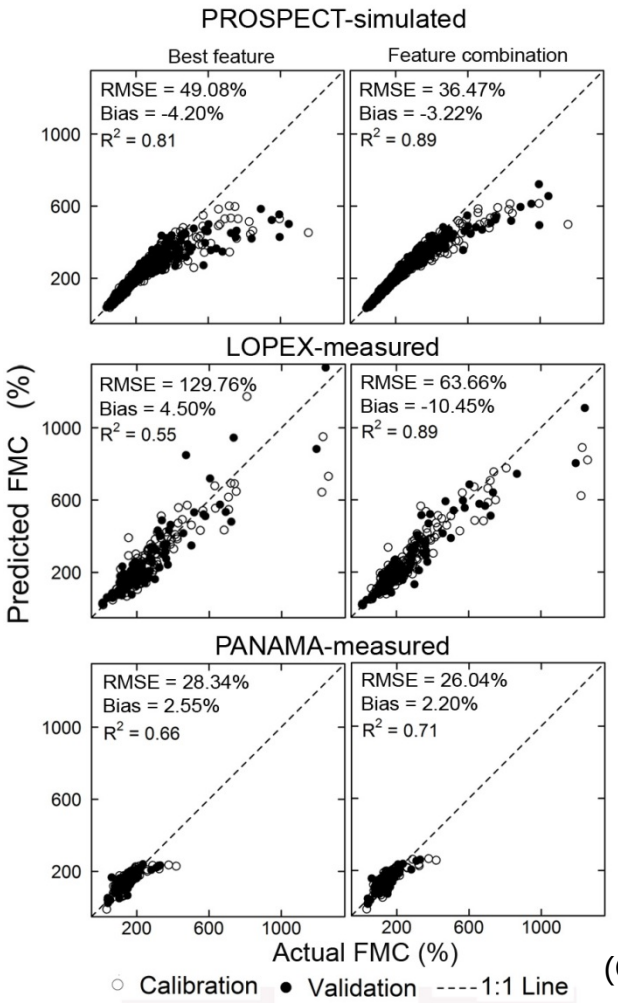
What spectral information do these wavelet features represent?



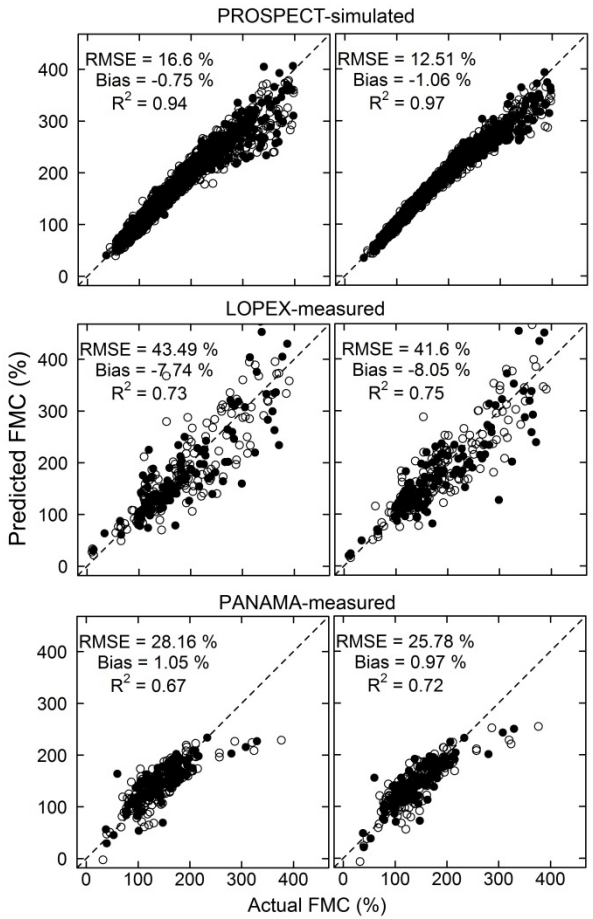
The wavelength position and scale of each feature are indicated by a vertical line and a Gaussian-shaped curve (wavelet function).

- We can separate information into different scales
- Higher scale features (in red) represent broader absorptions by water absorption
- Lower scale features (in blue) represent narrower absorptions by dry matter (e.g., lignin, cellulose, nitrogen)
- Simulations did not capture the common dry matter features from measured data

Predictions of FMC



FMC<400%

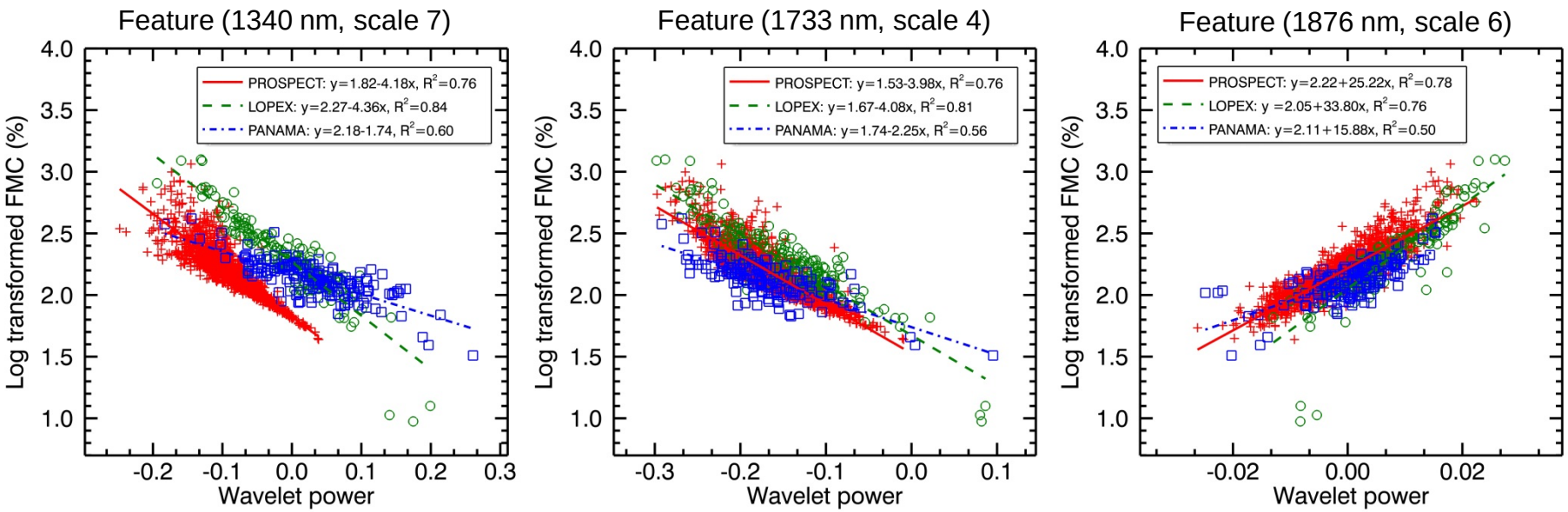


(Cheng et al., 2012)

- Feature combinations outperformed best features
- Close to 1:1 lines but some underestimations occurred at extremely high FMC values?

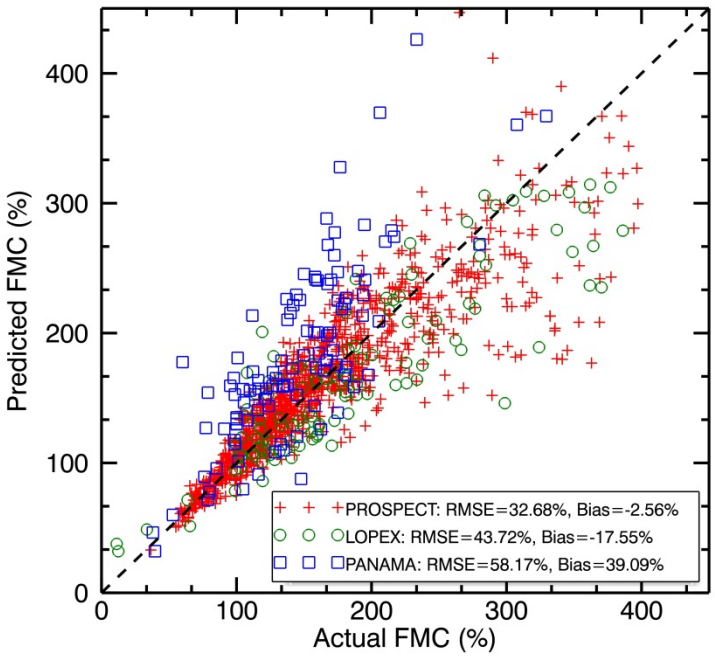
- Lower RMSE values
- Less underestimations

Regression models across data sets

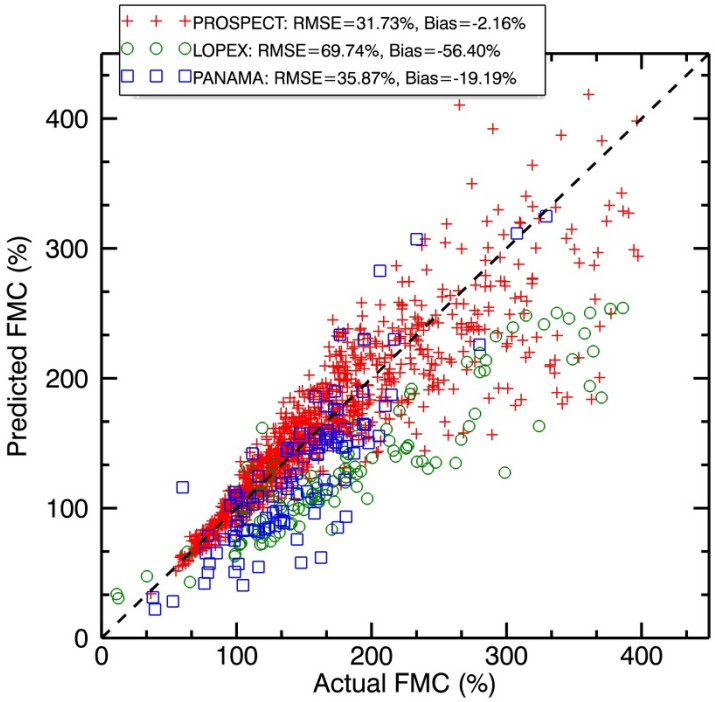


- Relationship between FMC and wavelet power
  - Generally log-linear for wide ranges
  - Linear when FMC<400% for LOPEX and 250% for PANAMA
- Point clouds overlapped most using feature (1733 nm, scale 4)

Transferability of regression models between data sets



Two features



Three features

- It is possible to transfer a model from simulations to measured data
- We may have to apply models based on feature combinations to individual data sets

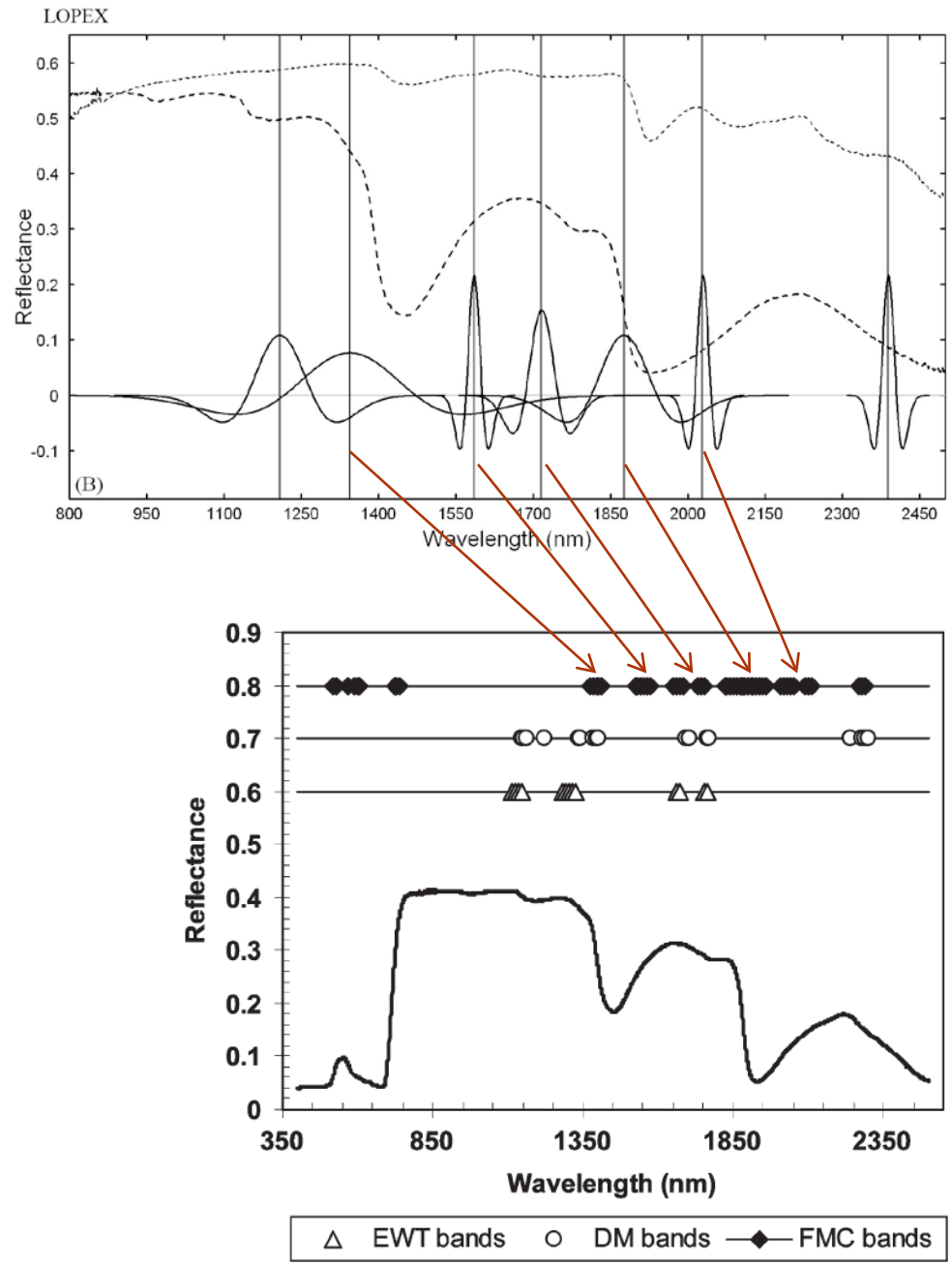
Comparison of CWA to GA-PLS based on the LOPEX data set

Best FMC estimation using GA-PLS (Li et al., 2007):
$R^2 = 0.893$, RMSE = 68.5%.

FMC estimation using a combination of wavelet features:
$R^2 = 0.89$, RMSE = 63.66%.

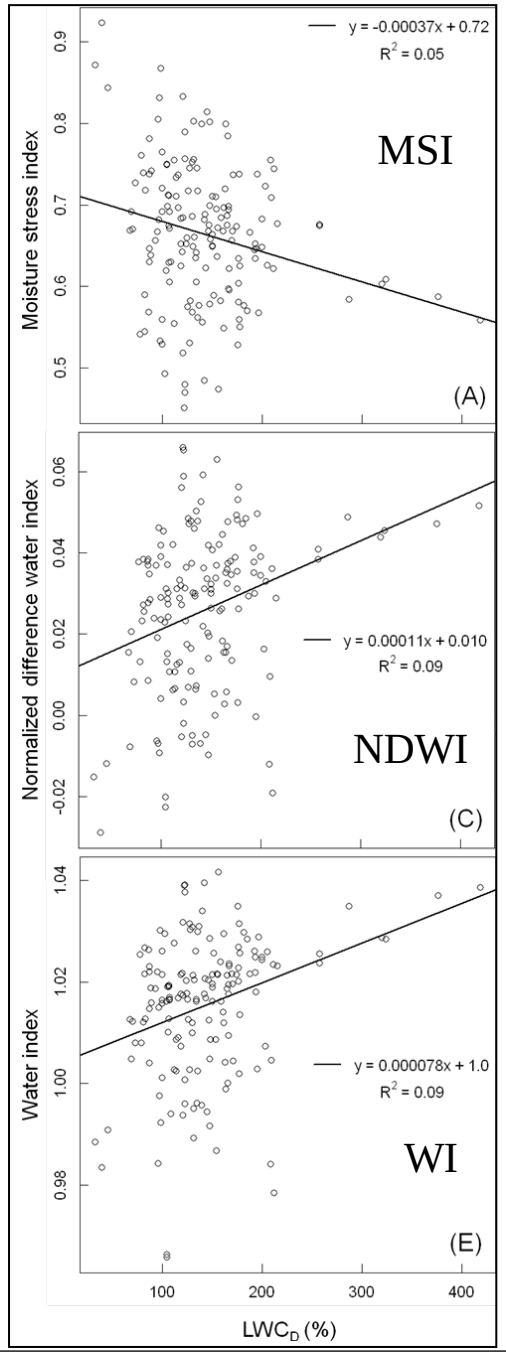
Results for the two methods are comparable:

- Close accuracy
- Overlapping spectral regions selected



(Li et al., 2007)

PANAMA



Spectral indices for FMC

- Broad-band water indices for the LOPEX data set (Danson & Bowyer, 2004): $R^2 = 0.54$, RMSE = 179.3%, but it worked poorly for PANAMA data set

  $MSI = R_{1600} / R_{820}$

  $NDWI = (R_{860}-R_{1240})/(R_{860}+R_{1240})$

  $WI = R_{900}/R_{970}$

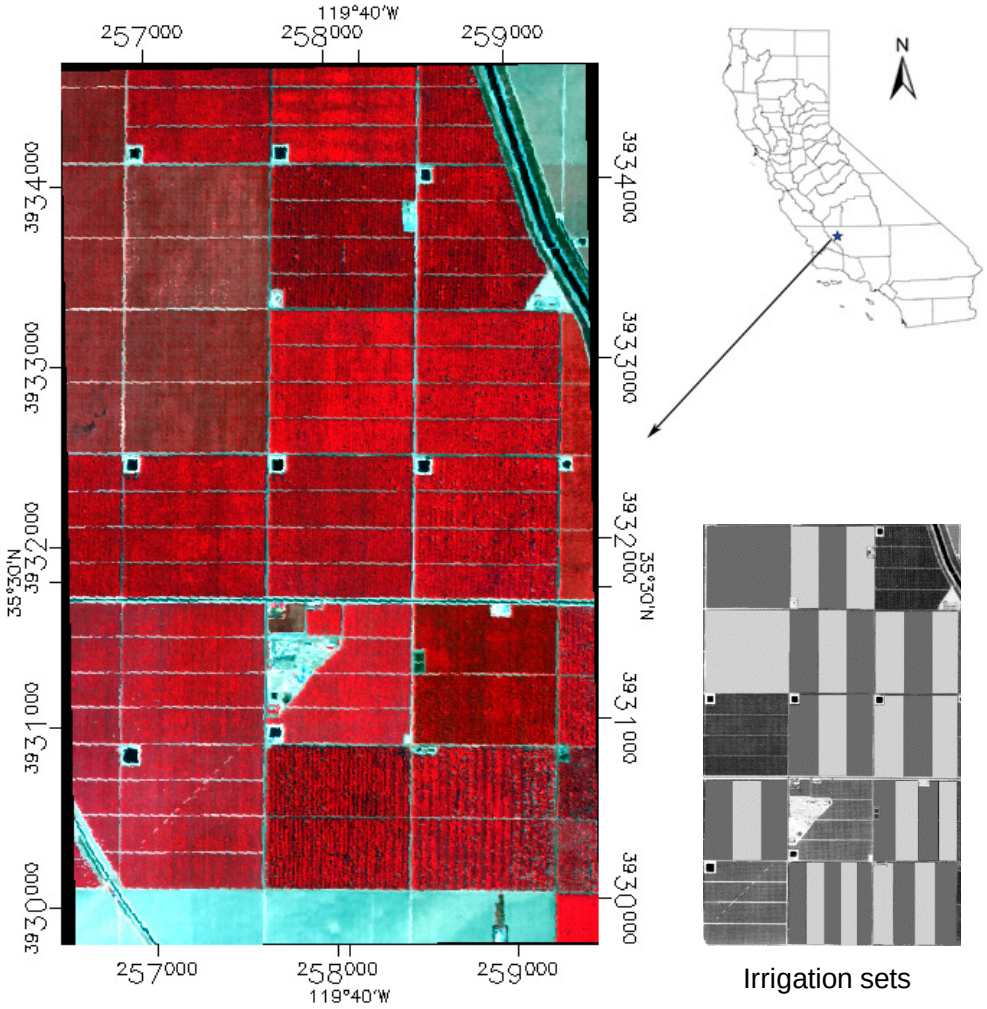
- The spectral index for FMC has to be optimized

- Feret et al. (2011) provided optimal indices for EWT and DMC, but not directly for FMC:
  - EWT: $(R_{1062}-R_{1393})/(R_{1062}+R_{1393})$
  - DMC: $(R_{1368}-R_{1722})/(R_{1368}+R_{1722})$

(Cheng et al., 2011)

A canopy-level study using AVIRIS imagery

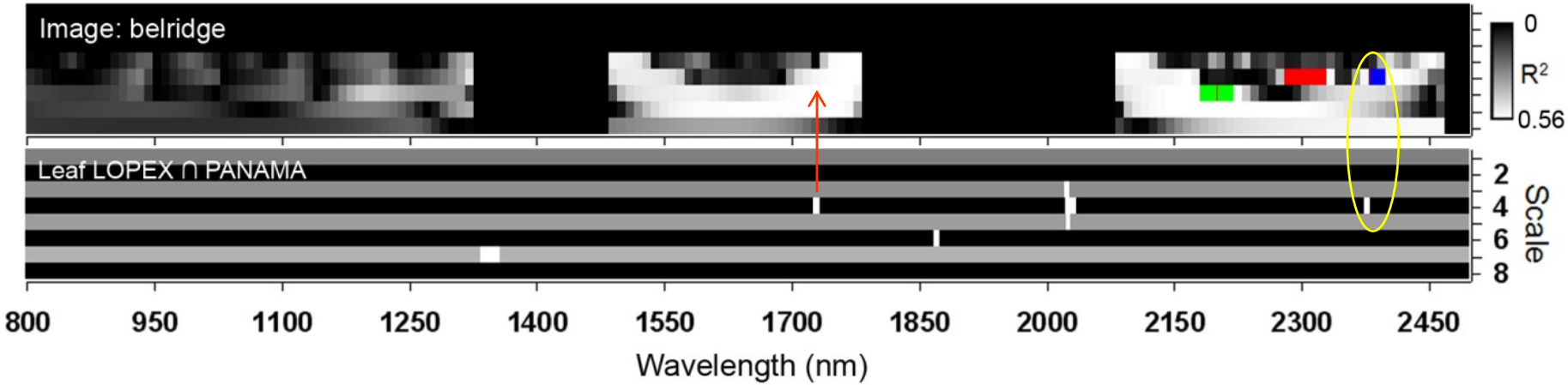
- Experiment was designed to examine the diurnal and seasonal variations in canopy water content
- Study area:
  - Irrigated Almond and pistachio orchards
- AVIRIS imagery
  - Pixel size: 8 m
  - Acquired twice in a day (11:00 and 15:00 PDT, June 30, 2011)
  - Images corrected for view angle effects
- Morning and afternoon FMC samples were combined together
- Preliminary results on FMC mapping using wavelet analysis and spectral indices

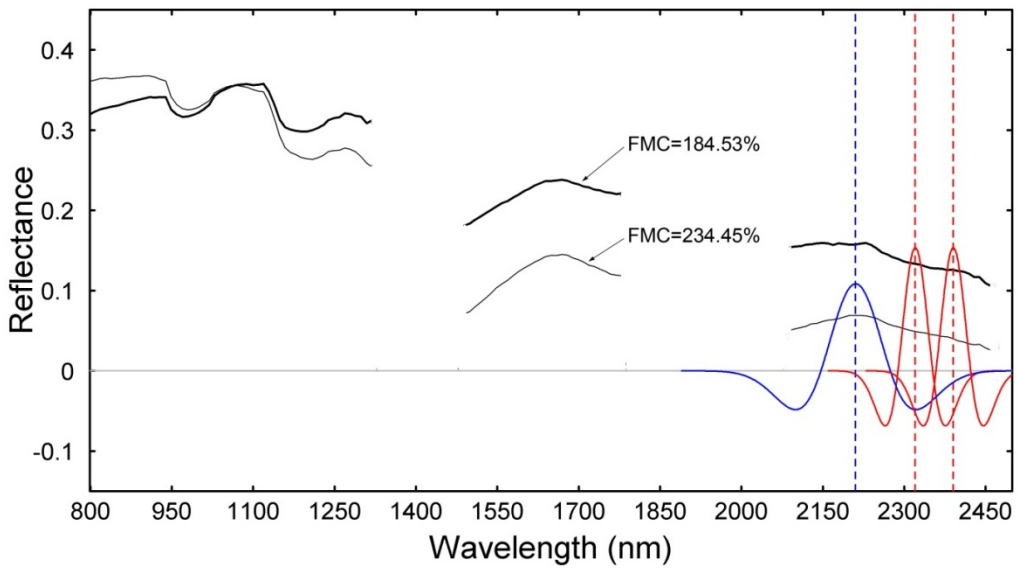


Irrigation sets

A false color composite image from AVIRIS (R: 860 nm, G: 650 nm, B: 550 nm)

Feature selection



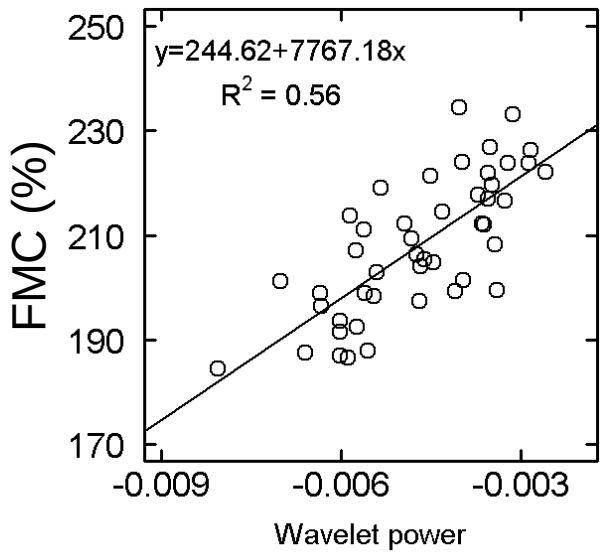


- Scales 1~3 were excluded (scale 3 produced noisy FMC maps)
- Centre features:
  - (2320 nm, scale 5)
  - (2210 nm, scale 6)
  - (2390 nm, scale 5) close to (2380 nm, scale 4) from the leaf study
- All features were related to dry matter absorption and appeared at higher scales than those from the leaf study

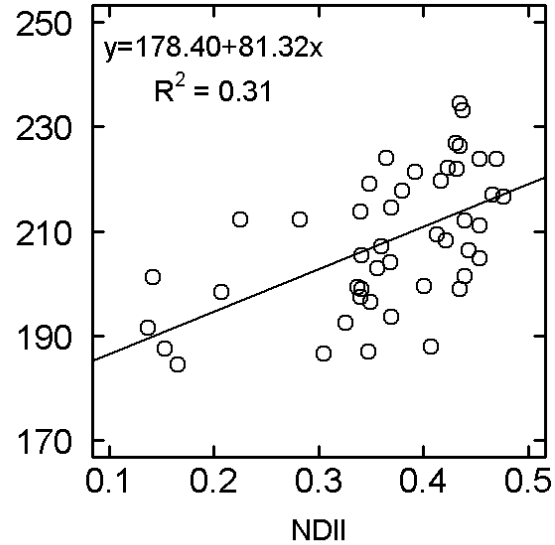
Performance of wavelet features

Spectral features	R^2
(2320, 5)	0.56
(2210, 6)	0.41
(2390, 5)	0.40
All wavelet features	**0.58**
NDII	0.31
NDWI	0.20
WI_970	0.17
WI_1180	0.21
All indices	**0.47**
All	**0.66**

- Higher correlations than common water indices
- Improved when combined with vegetation indices
- Linear correlation with FMC

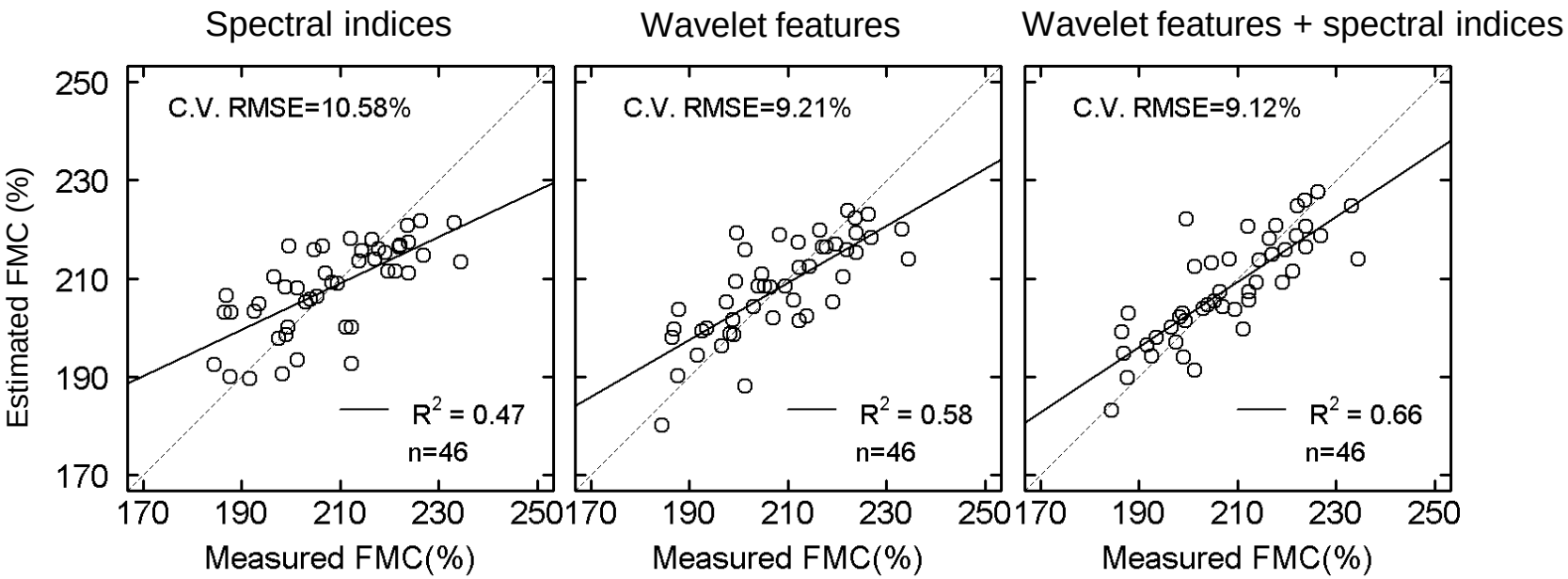


Best wavelet feature



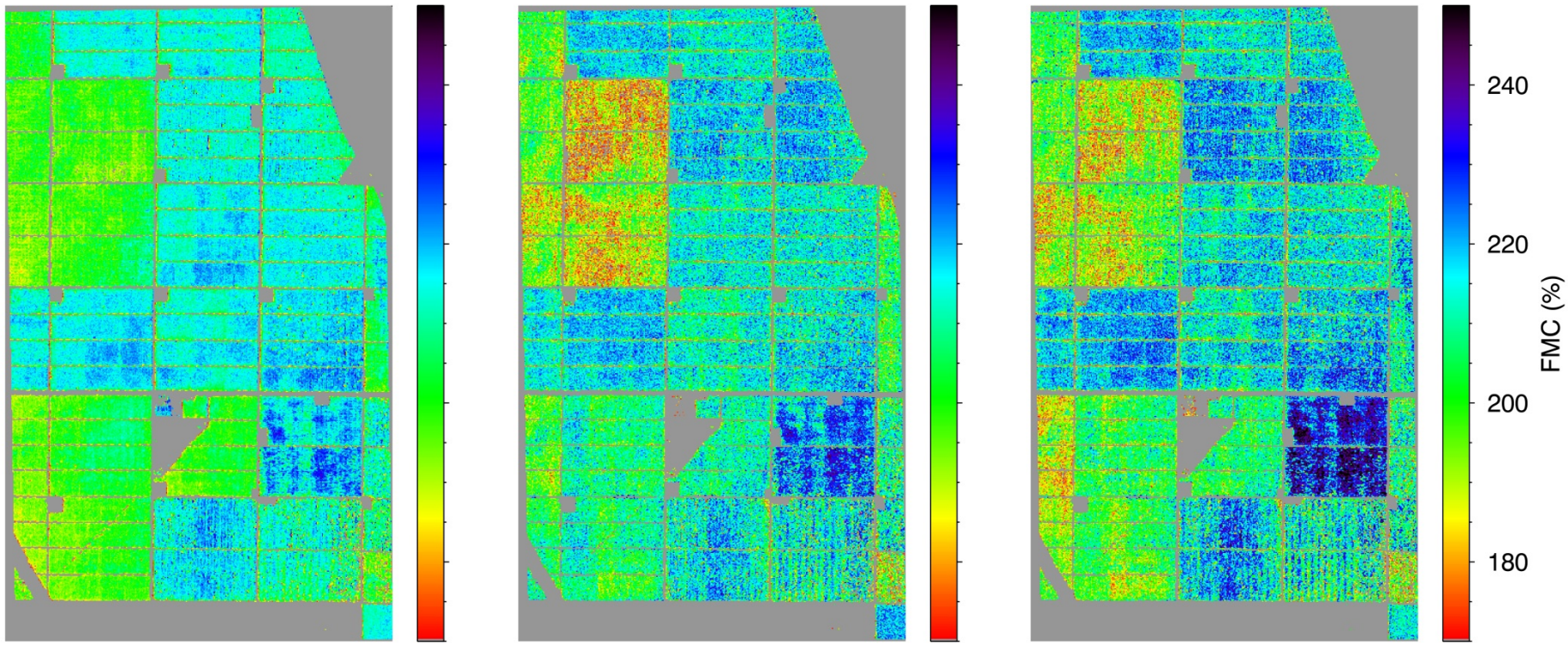
Best spectral index

Estimations using different spectral features



- Greater improvement in R^2 than in RMSE due to low variance in FMC data (mean=208.16%, s.d.=13.15%)
- Wavelet features helped improve the sensitivity of spectral responses to FMC variation. This is more obvious on FMC maps.

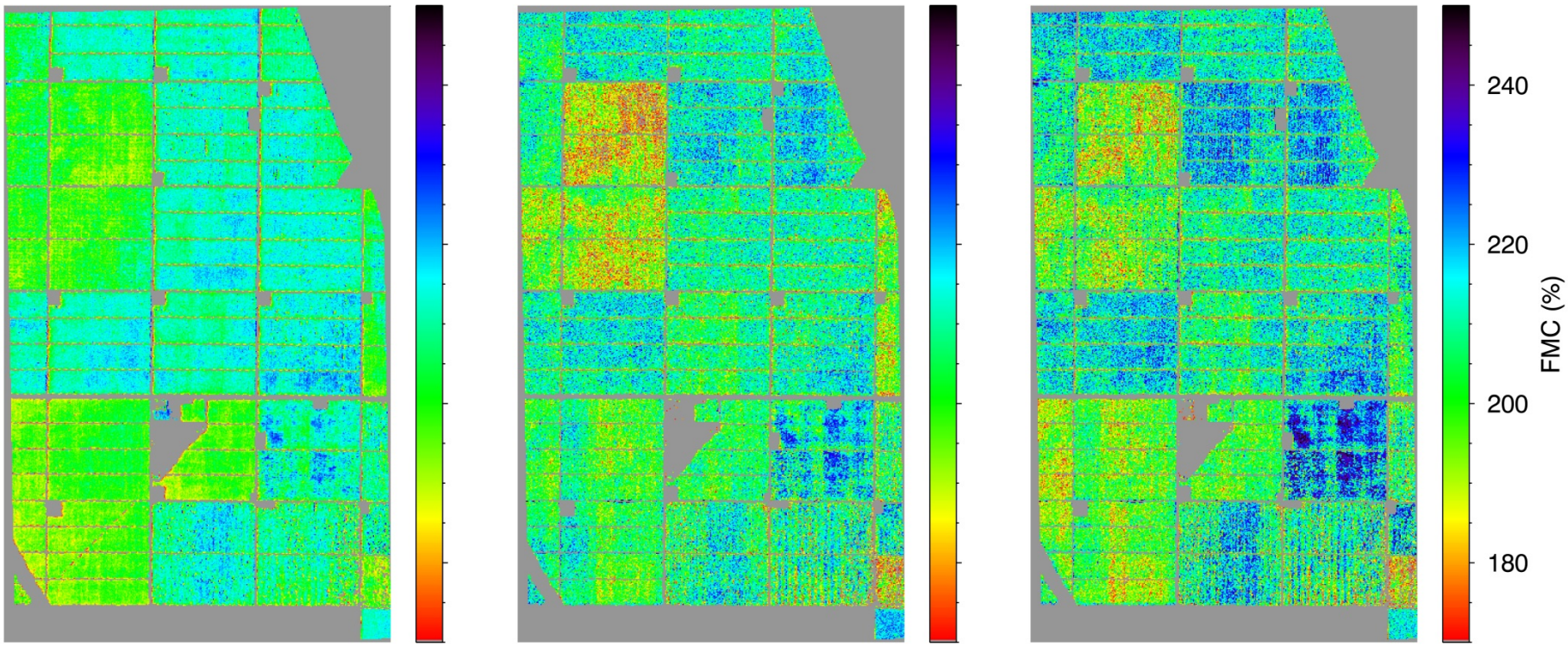
Morning FMC maps using different combinations of spectral features



Spectral indices | Wavelet features | Wavelet features + spectral indices

- FMC Maps produced by using and adding wavelet features have broader ranges as shown by field data
- The improvement suggests the wavelet approach is promising and it can be integrated with the spectral index approach

Afternoon FMC maps using different combinations of spectral features



Spectral indices | Wavelet features | Wavelet features + spectral indices

- Spatial patterns are similar to those on morning FMC maps
- FMC was generally lower in the afternoon, representing diurnal FMC variation within four hours

Challenges of using imaging spectroscopy data

- Take advantage of full-spectrum information
  - Band-based or spectral region-based?
  - Learn from the transition from pixel-based to object-based for high spatial resolution imagery
- Fidelity of spectral data is important for the use of some absorption features
- Identification of robust spectral regions
  - Across different airborne or spaceborne instruments
  - Across different illumination conditions

(http://hyspiri.jpl.nasa.gov)

The HyspIRI satellite mission:

- 380-2500 nm with 10 nm steps
- Revisit frequency of 19 days
- 60 m pixel size

Conclusions

- Wavelet features are effective spectral metrics for the estimation of FMC across a wide range of leaf types.
- The wavelet approach demonstrated leaf FMC variation was sensitive to both broad-range water absorptions and narrow-range dry matter absorptions.
- Canopy FMC variation was sensitive to dry matter absorptions but the scales were higher than those at leaf level.
- The wavelet approach showed promise for mapping FMC over a large area using imaging spectroscopy data.

Acknowledgement

- National Science & Engineering Research Council of Canada
- NASA Terrestrial Hydrology Program (#NNX09AN51G)
- USDA Specialty Crop Research Initiative (SCRI #0215934)

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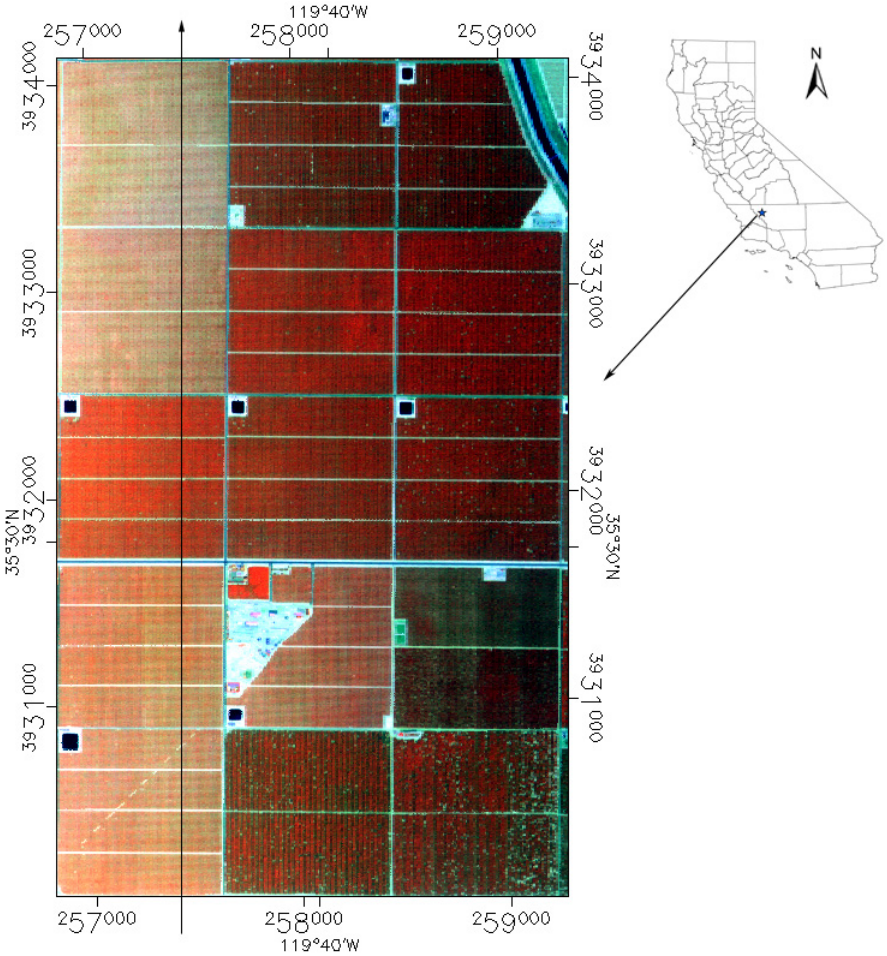

2010 MASTER image

Relationship between FMC and wavelet power