Linking Seasonal Foliar Chemistry to VSWIR-TIR Spectroscopy Across California Ecosystems

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Foliar Chemistry

- Foliar chemistry provides an insight into the quality of vegetation and nutrient cycles
  - Chlorophyll –> Levels of productivity
  - Nitrogen –> Indicator of photosynthetic and growth rates
  - Lignin –> Rate of litter decomposition

- Spectroscopy can reduce sample preparation and speed up analysis (Lawler et al., 2006)
- Spectroscopy uses relationships derived between spectra and laboratory measured components to then predict unknown content of components

VSWIR Spectroscopy

- Most spectroscopy studies use the Visible Near Infrared/Short Wave Infrared (VSWIR) spectrum
- Plant Biochemical:
  - Nitrogen (Bolster et al. 1996; Doughty et al. 2011; Ferwerda et al., 2005; Martin et al. 2008)
  - Lignin and Cellulose (Kokaly and Clark, 1992; Asner et al., 2011; Martin & Aber, 1997)
  - Chlorophyll (Ustin et al., 2009; Doughty et al 2009; Asner et al., 2011)
- Plant Biophysical: Specific Leaf Area, Water Content
  - (Ceccato et al., 2001; Doughty et al., 2009; Martin et al., 2008; Asner et al., 2011)
- VSWIR spectrum dominated by water and pigment absorption (Ribeiro da Luz and Crowley, 2010)

TIR Spectroscopy

- Thermal Infrared (TIR) spectrum
- Spectral features of water content, cellulose, cutin, xylan, silica, and oleanolic acid present
  - (Fabre et al., 2011; Ribeiro da Luz and Crowley 2007; Ullah et al., 2014)
- TIR incorporation delayed by limited availability of sensors, subtle features of plants, low signal to noise ratio

- Integrating VSWIR and TIR
  - Limited knowledge on synergies
  - Play on strengths and avoid problem areas of each spectrum

Research Questions

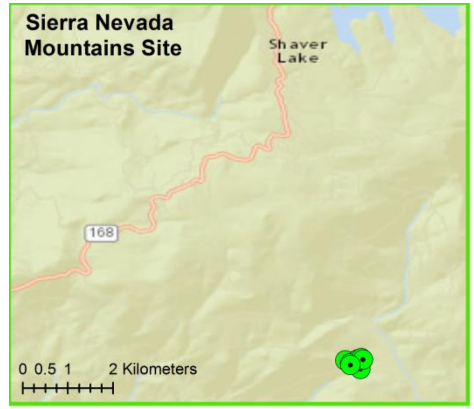
1. What are the capability of VSWIR and/or TIR spectra to predict leaf levels of lignin, cellulose, nitrogen, water content, and leaf mass per area?
2. How do these predictive relationships change seasonally and among plant functional types?
3. Can these relationships between spectra and foliar chemistry be extended to the reduced spectral resolution available in airborne and space-borne sensors?
   - Airborne Visible/Infrared Imaging Spectrometer (AVIRIS)
   - Hyperspectral Thermal Emission Spectrometer (HyTES)
   - Hyperspectral Infrared Imager (HyspIRI)

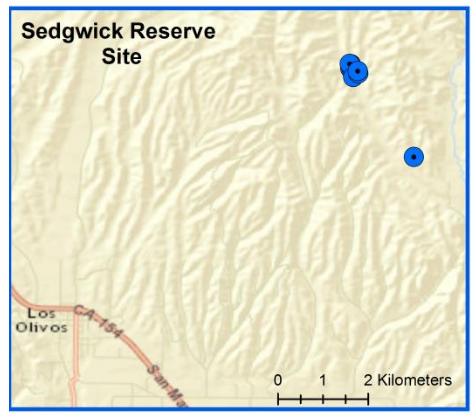
Study Sites

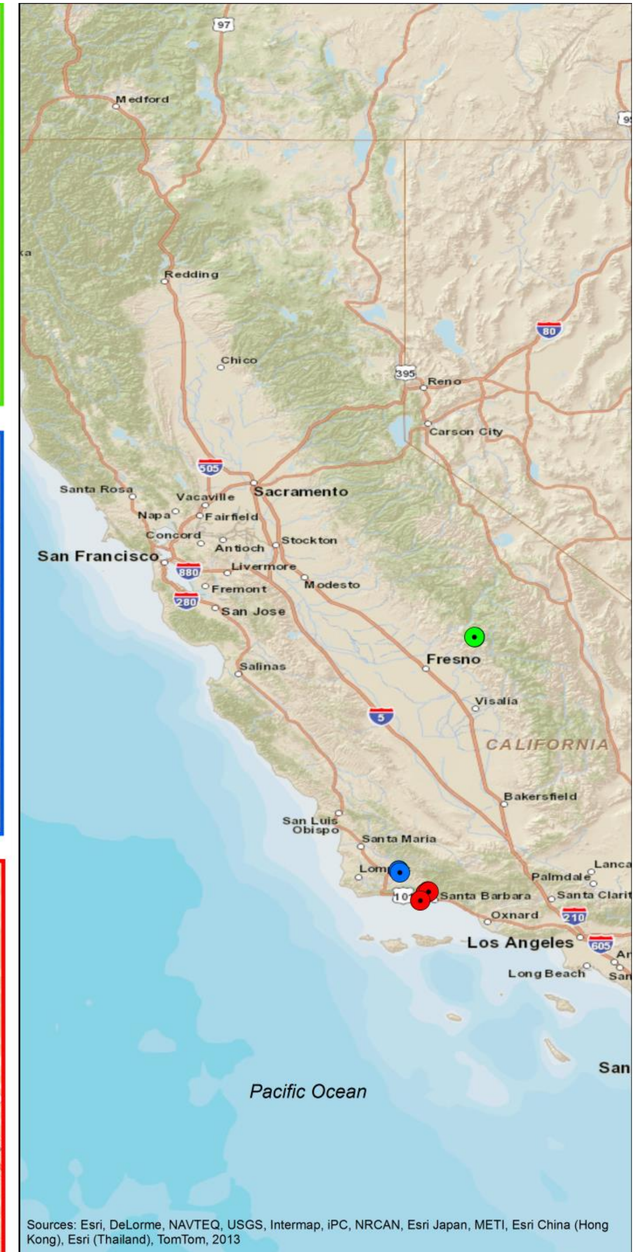
- **Sierra Nevada Mountains Site:**
  - Elevation: 1400m
  - Mixed conifer forest

- **Sedgwick Reserve Site:**
  - Elevation: 382 & 400 m
  - Coastal sage scrub & oak woodland

- **Coastal Santa Barbara Site:**
  - Elevation: 5, 515, & 1080m
  - Chaparral







Field Collection

- 16 Species
- 3 Replications
- Young and Old Leaf Sample
- Spring:
  - Santa Barbara: 4/1/13
  - Sierra Nevada: 4/20/13
  - Sedgwick Reserve: 4/21/13
- Summer:
  - Santa Barbara: 6/3/13
  - Sierra Nevada: 6/8/13
  - Sedgwick Reserve: 6/9/13
- Fall:
  - Santa Barbara: 10/13/13
  - Sierra Nevada: 11/02/13
  - Sedgwick Reserve:11/03/13

Species	Common Name	Abb.
Adenostoma fasciculatum	Chamise	ADFA
Arctostaphylos glandulosa	Manzanita	ARGL
Baccharis pilularis	Coyote brush	BAPI
Ceanothus cuneatus	Buck-brush Ceanothus	CECU
Ceanothus megacarpus	Big-pod Ceanothus	CEME
Ceanothus spinosus	Green-bark Ceanothus	CESP
Heteromeles arbutifolia	Toyon	HEAR
Umbellularia californica	Bay laurel	UMCA
Abies concolor	White Fir	ABCO
Pinus lambertiana	Sugar Pine	PILA
Pinus ponderosa	Ponderosa Pine	PIPO
Calocedrus decurrens	Incense cedar	CADE
Quercus agrifolia	Coast live oak	QUAG
Quercus douglasii	Blue Oak	QUDO
Quercus lobata	Valley Oak	QULO
Salvia leucophylla	Purple Sage	SALE

Data Collected

- **VSWIR Spectra:** Analytical Spectra Devices (ASD) measuring 0.35 to 2.5 μm
- **Thermal Spectra:** Nicolet measuring 2.5 to 15.4 μm
- **Nitrogen:** combustion method using NA 1500 Nitrogen and Carbon Analyzer
- **Lignin and Cellulose:** sequential acid digestion using Ankom Fiber Analyzer
- **Water Content:** 100*((wet leaf mass – dry leaf mass)/ wet leaf mass)
- **Leaf Mass per Area (LMA)**
- **Leaf Thickness**




PLS Regression

- Partial Least Squares Regression (PLSR)
- Similar to traditional regression models but is able to analyze many, noisy, correlated variables in both X and Y

- Determined number of factors using leave-one-out cross validation and fulfilling these requirements:
  - Smallest Number of Factors
  - Smallest RMSE
  - Highest Percent Variation Explained
- Models were validated by holding out 10% of the data during each iteration, until all samples had been removed once

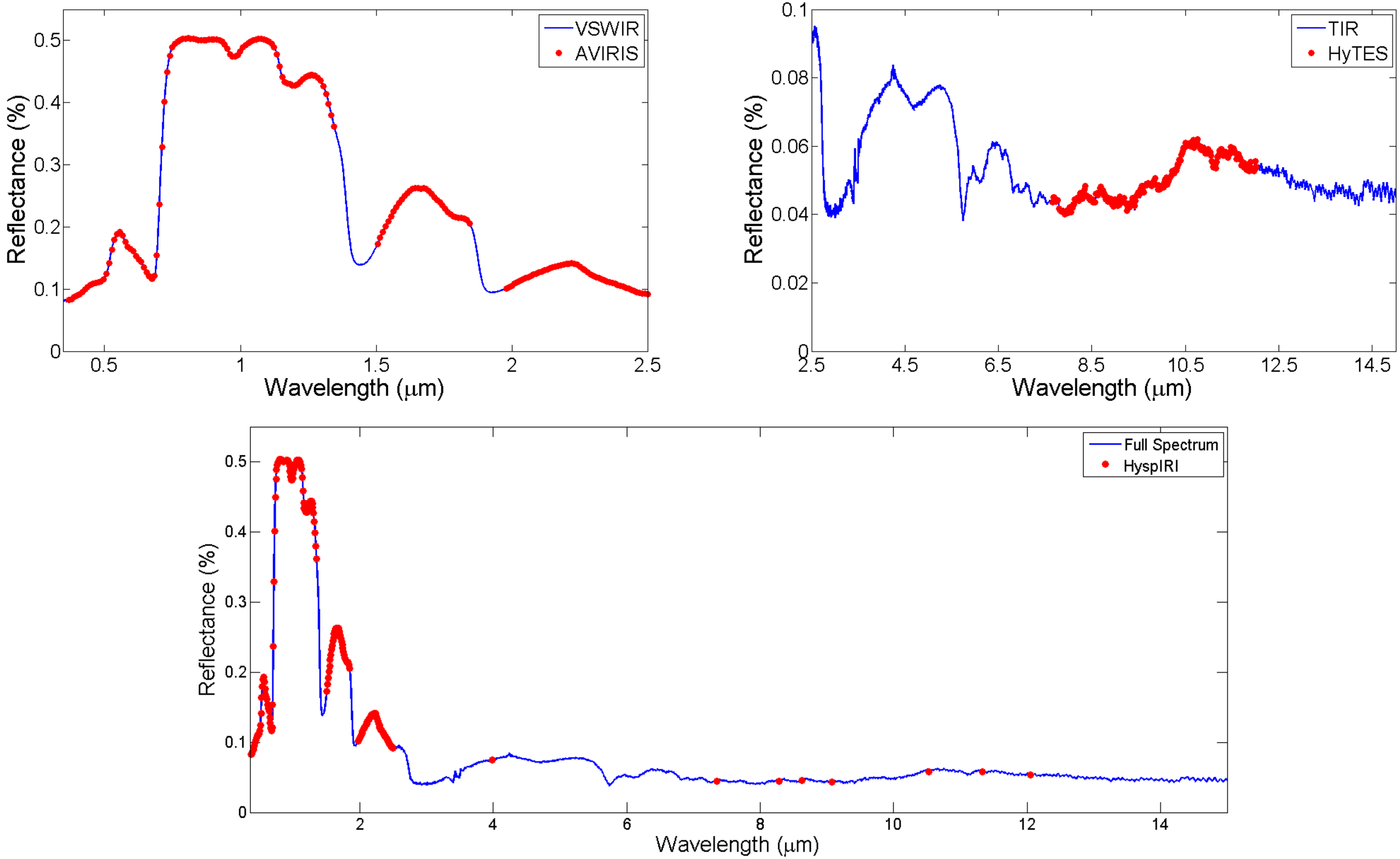
PLS Regression

- All Samples
- Seasons: Spring Summer Fall

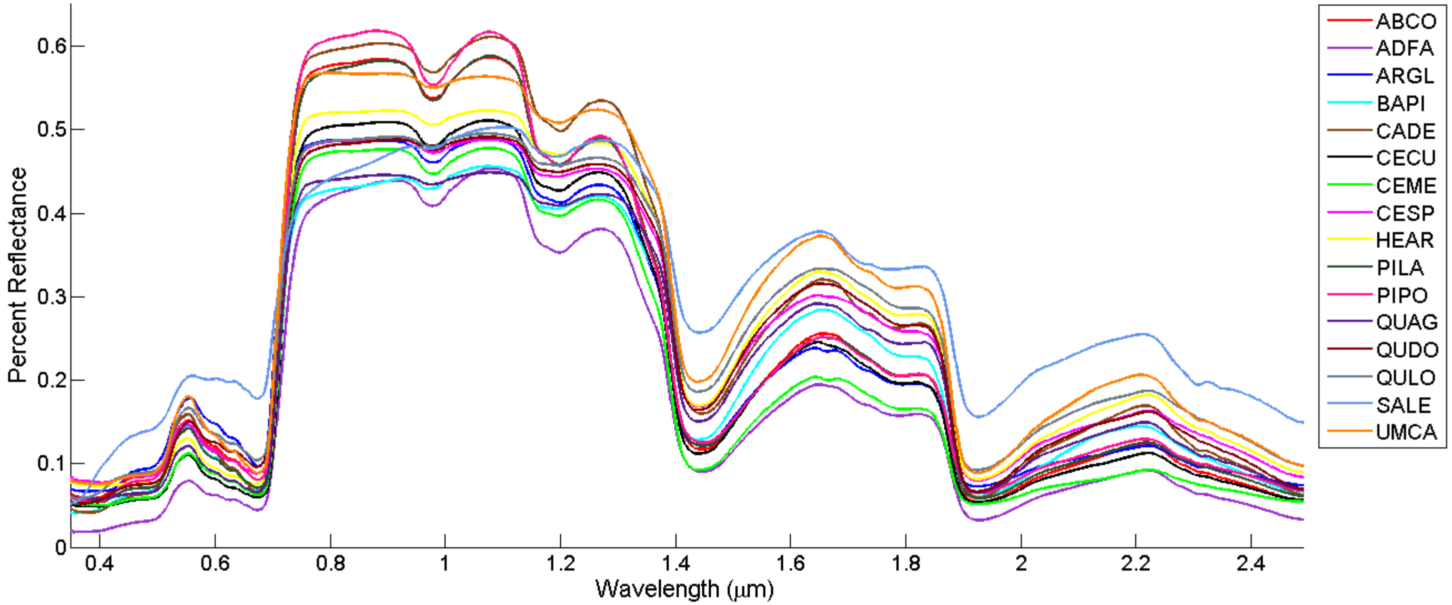
- Plant Functional Types

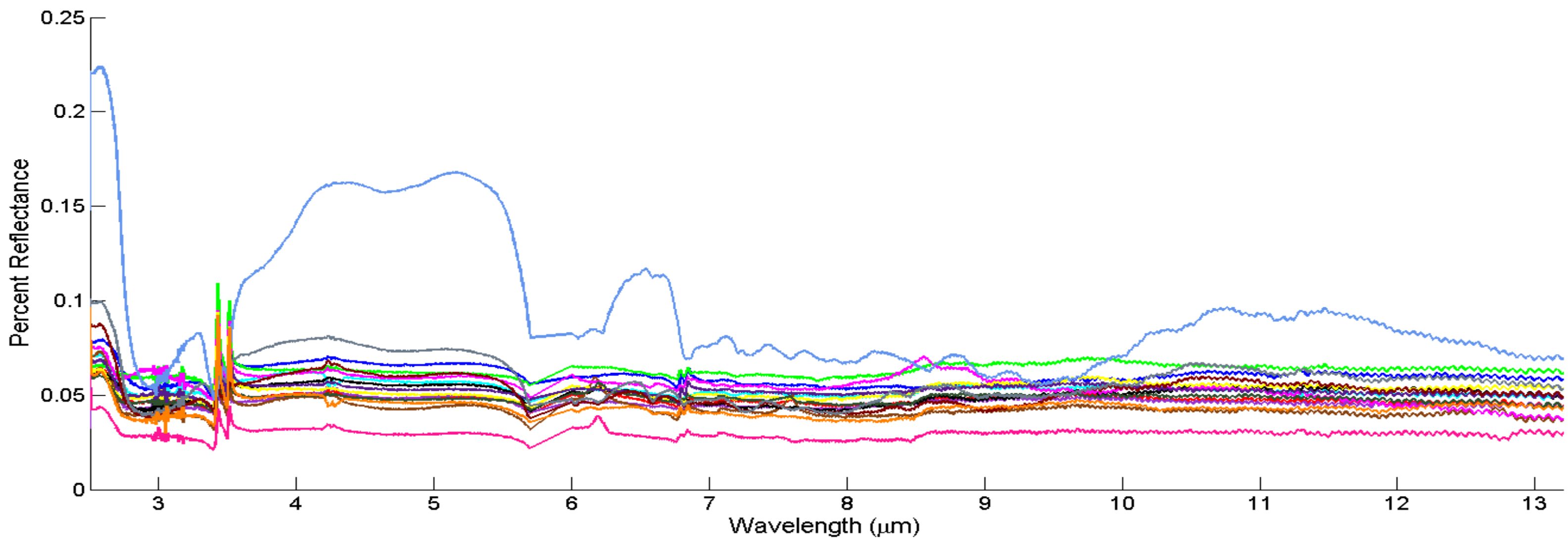
Broadleaf Deciduous	Broadleaf Evergreen		Needleleaf Evergreen
Blue Oak (QUDO)	Manzanita (ARGL)	Coyote brush (BAPI)	White Fir (ABCO)
Valley Oak (QULO)	Buck-brush Ceanothus (CECU)	Toyon (HEAR)	Sugar Pine (PILA)
Purple Sage (SALE)	Big-pod Ceanothus (CEME)	Coast Live Oak (QUAG)	Ponderosa Pine (PIPO)
	Green-bark Ceanothus (CESP)	Bay Laurel (UMCA)	Incense Cedar (CADE)
			Chamise (ADFA)

PLS Regression

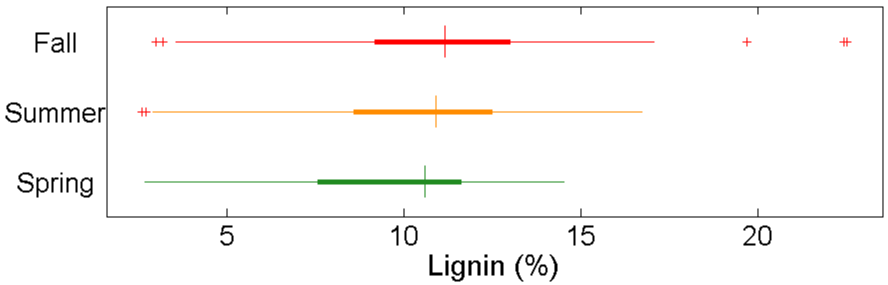


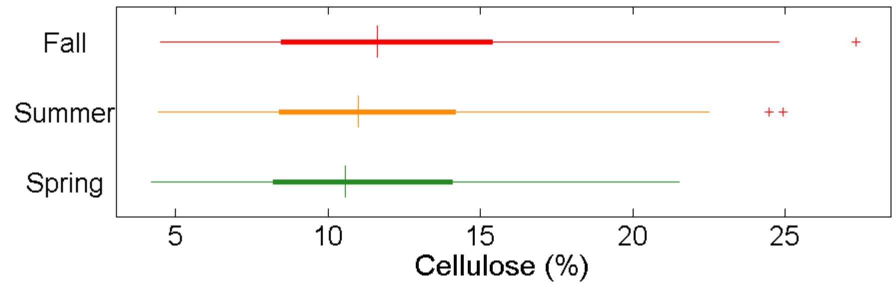
Spectra

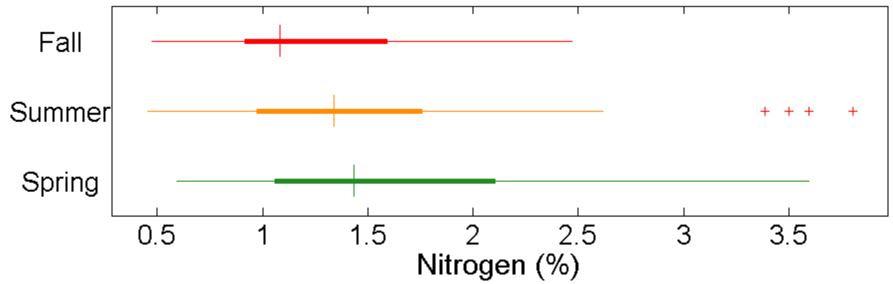

0.6
0.5
0.4
0.3
0.2
0.1
0
Percent Reflectance
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
2.2
2.4
Wavelength (µm)
ABCO
ADFA
ARGL
BAPI
CADE
CECU
CEME
CESP
HEAR
PILA
PIPO
QUAG
QUDO
QULO
SALE
UMCA

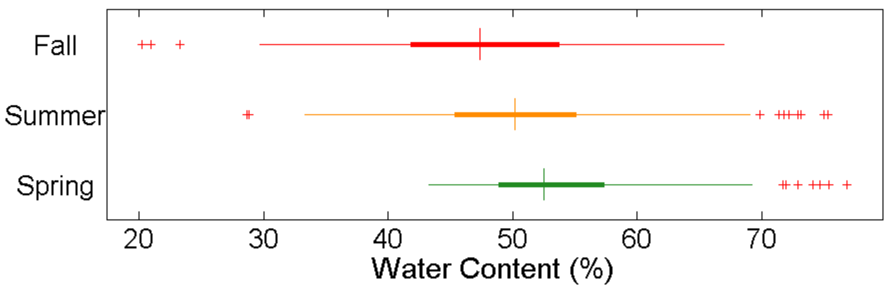

0.25
0.2
0.15
0.1
0.05
0
Percent Reflectance
3
4
5
6
7
8
9
10
11
12
13
Wavelength (µm)

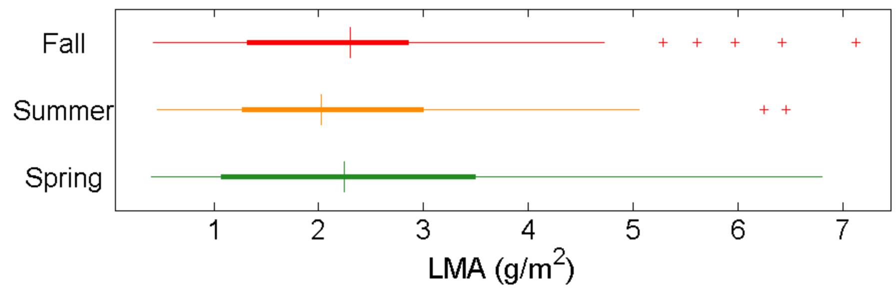
Biochemistry



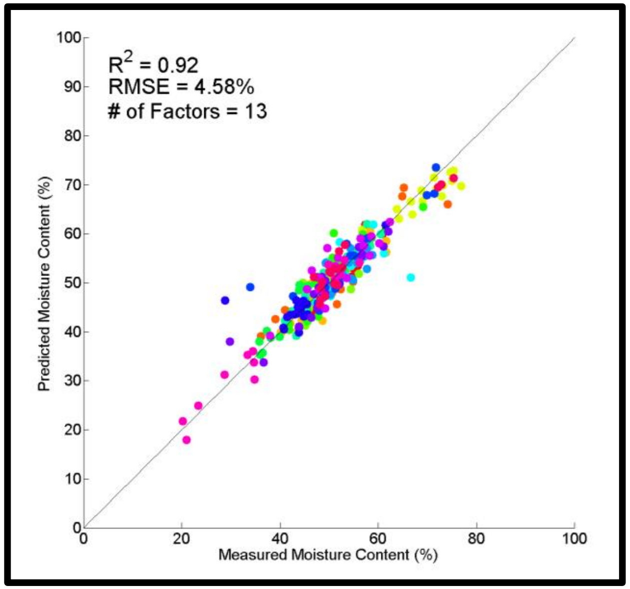


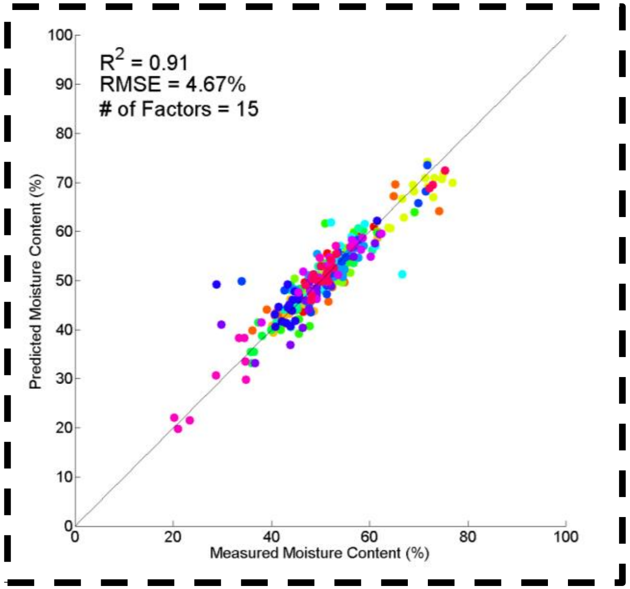


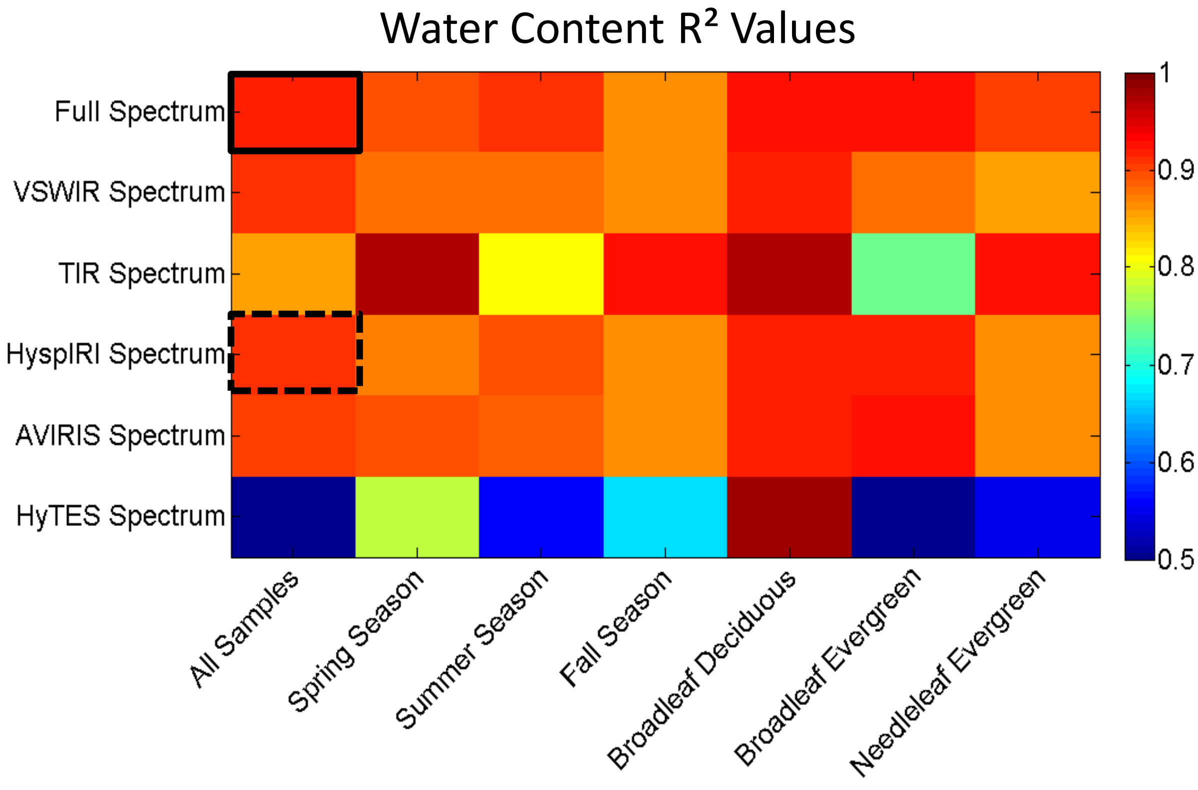




All Water Content Models

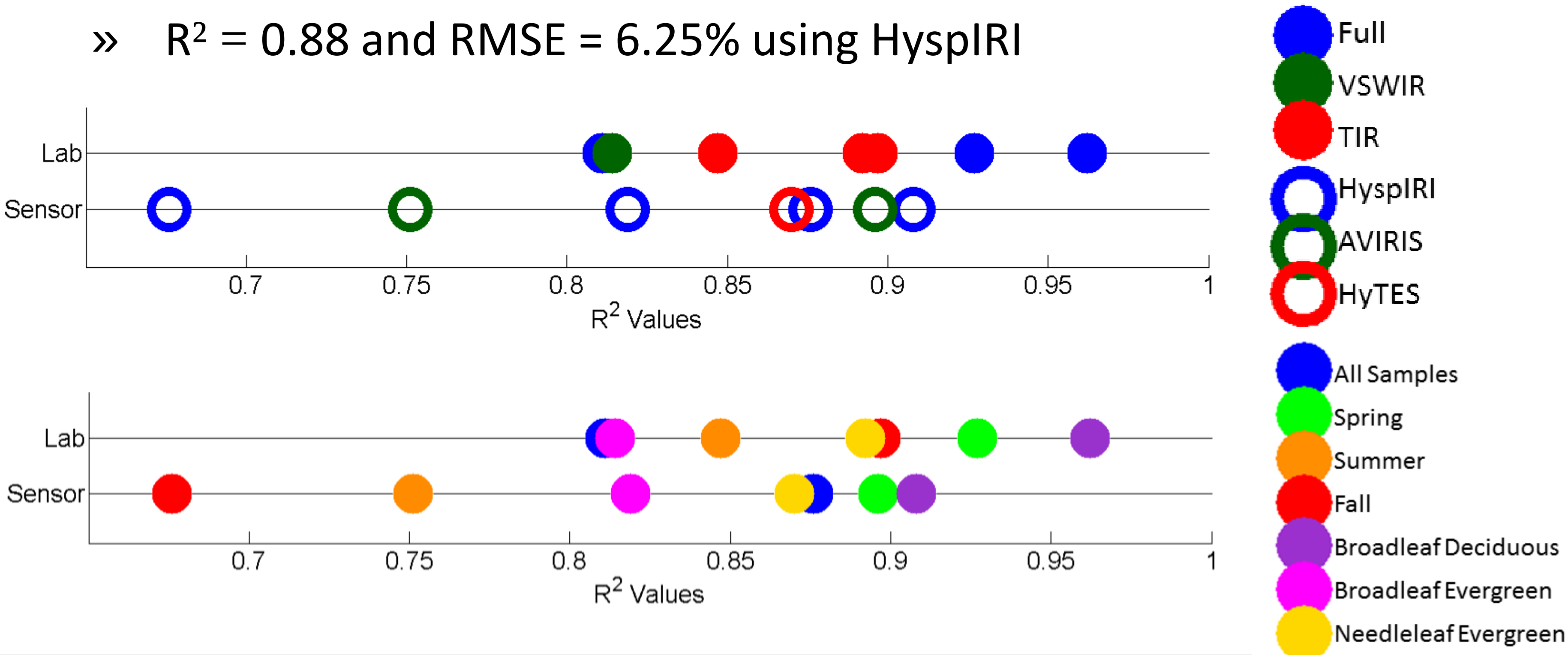






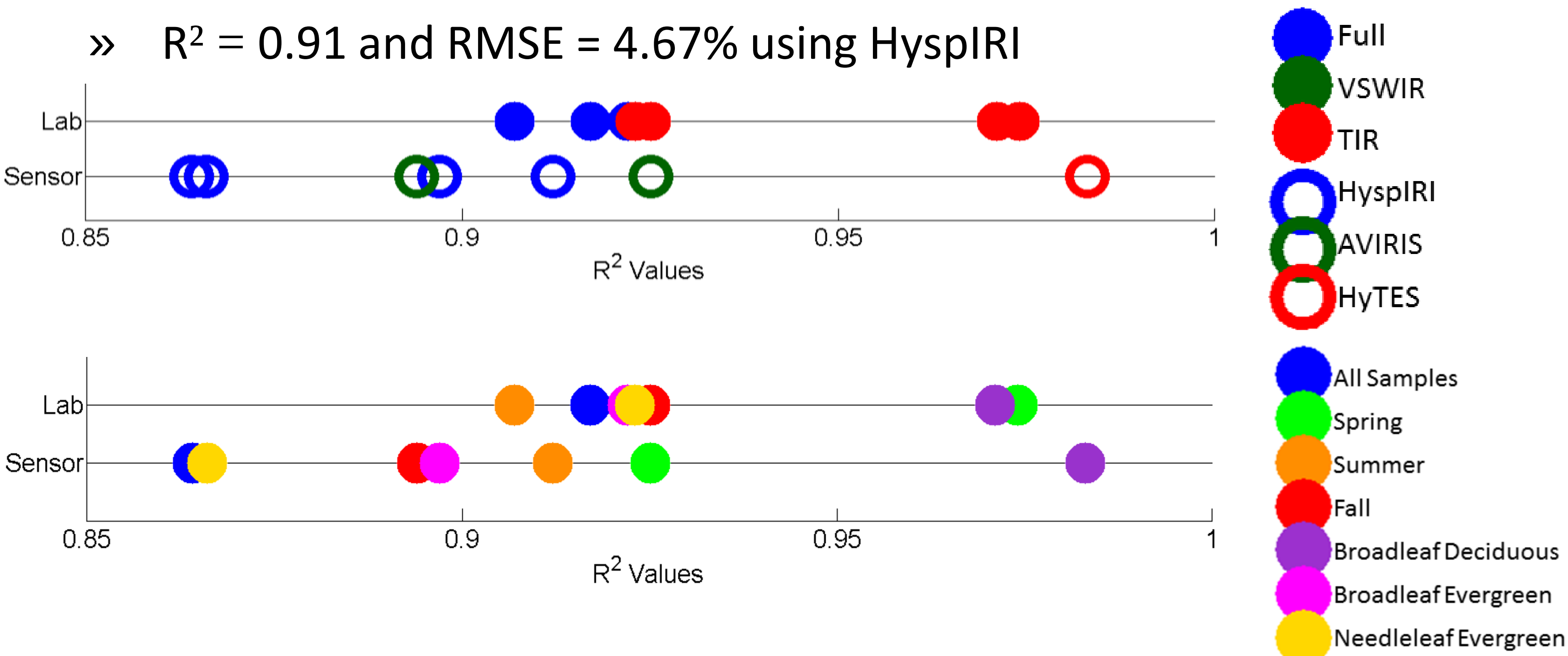
Nitrogen

- Majority of models used:
  - » TIR or full spectrum for Laboratory spectra
  - » HyspIRI for sensor simulated spectra
- While all samples models decreased R^2 still appropriate for predicting:
  - » R^2 = 0.88 and RMSE = 6.25% using HyspIRI



Water Content

- Majority of models used:
  - » TIR for laboratory spectra
  - » HyspIRI for sensor simulated spectra
- All samples models had lower R^2 but still appropriate for predicting:
  - » R^2 = 0.91 and RMSE = 4.67% using HyspIRI



Other

- LMA:
  - » Top model results: $R^2 = 0.68$ to 0.98
  - » Majority spectra used TIR and HyspIRI
  - » Top model: Broadleaf deciduous plant functional type using HyTES
- Lignin:
  - » Top model results: $R^2 = 0.68$ to 0.93
  - » Majority spectra used Full and HyTES
  - » Top model: Spring $R^2 = 0.91$ and RMSE = 6.91% using HyTES
- Cellulose:
  - » Top model results: $R^2 = 0.75$ to 0.98
  - » Majority spectra used Full, VSWIR, and AVIRIS
  - » All samples models: $R^2 = 0.82$ and RMSE = 7.95% using AVIRIS

Research Questions Revisited

1. What are the capability of VSWIR and/or TIR spectra to predict leaf levels of lignin, cellulose, nitrogen, water content, and leaf mass per area?
   – Top models showed high precision and accuracy for all biochemicals
   – Majority of models used TIR or full spectrum for Laboratory spectra
   – Majority of models used HyspIRI for sensor simulated spectra
2. How do these predictive relationships change seasonally and among plant functional types?
   – Model precision varied by season and across plant functional types
   – For Cellulose, Nitrogen, and Water Content all samples model appropriate for prediction
   – Lignin and LMA best predicted if divided into subset

Research Questions Revisited

3. Can these relationships between spectra and foliar chemistry be extended to the reduced spectral resolution available in airborne and space-borne sensors?
   - » Simulated sensor spectra models had high precision & accuracy
   - » Next step apply to the aerial imagery for real atmosphere effects
   - » In summary, the TIR spectrum could augment the VSWIR in advancing identification of leaf biochemical and physical properties even at reduced spectral resolutions

Questions?

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