

# Retrieving Ecosystem Light Use Efficiency Using Hyperion

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# Introduction

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We ask the question:

Can a single algorithm driven by hyperspectral satellite data provide an estimate of carbon flux variables globally?

Why use a single algorithm?

Some MODIS products (such as LAI,  $f_{PAR}$ , or GPP) use a land cover classification as a first step to decide the algorithm/coefficients used in the retrieval.

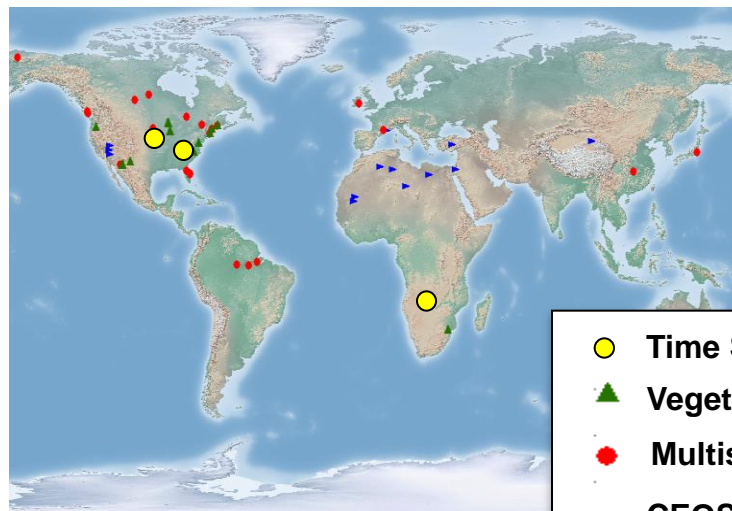
Accuracy of MODIS Collection 5 Land Cover Type product (MCD12Q1) is estimated to be 75%

<http://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD12>

Algorithms requiring land cover classification will have questionable results for the 25% mis-classified pixels

# Remote Sensing of Fluxes: Hyperion and Fluxnet

- Can statistical approaches use spectral information to adjust for site differences but capture seasonal changes in flux variables?
- To address this question we examined a number of different sites with different vegetation types throughout the year.
  - Hyperion on EO-1 can provide consistent repeated observations of widely distributed sites
  - Spectra are averages of uniform regions around flux tower
- We combined satellite imagery with carbon flux data from the AmeriFlux and CarboAfrica networks



- Time Series Study Sites
- ▲ Vegetation Study Sites
- Multisite Study Sites
- ▶ CEOS Calibration Sites

# Light Use Efficiency Model

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This study looks at the Light Use Efficiency ( $\varepsilon$ ) at midday (11:00 AM to 1:00 PM local time)

$$\text{GEP} = \varepsilon f_{\text{APAR}} \text{PAR}_{\text{in}} \quad \text{or}$$

$$\varepsilon = \text{GEP} / (f_{\text{APAR}} \text{PAR}_{\text{in}})$$

Where:

GEP is the gross ecosystem production

PAR<sub>in</sub> is the incident Photosynthetically Active Radiation (PAR)

$f_{\text{APAR}}$  is the fraction of PAR absorbed by vegetation

$\varepsilon$  is the light use efficiency, the conversion factor between energy and absorbed carbon

- In existing models  $\varepsilon$  is assigned a maximum value based on cover type and downregulated based on responses to meteorological variables such as temperature and humidity

# Multitemporal Data for 5 Towers

Data collected in 2008-2009 (n = 47 total)

Duke Forest, NC, USA

- Hardwood – n=5

- Loblolly pine – n=5

Mongu, Zambia

- Miombo woodland – n=23

Konza Prairie, KS, USA

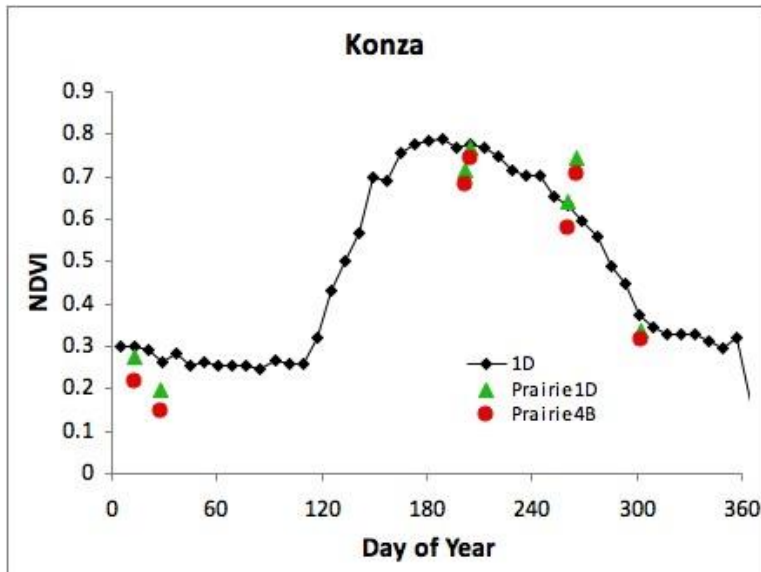
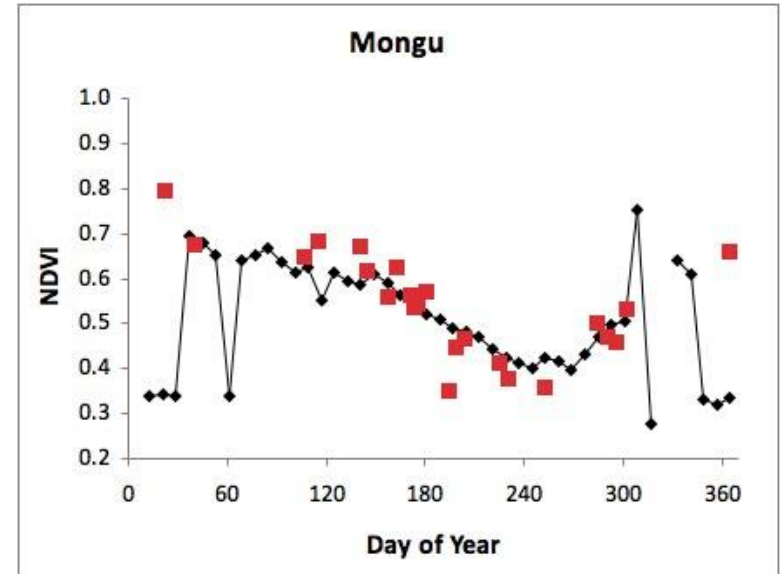
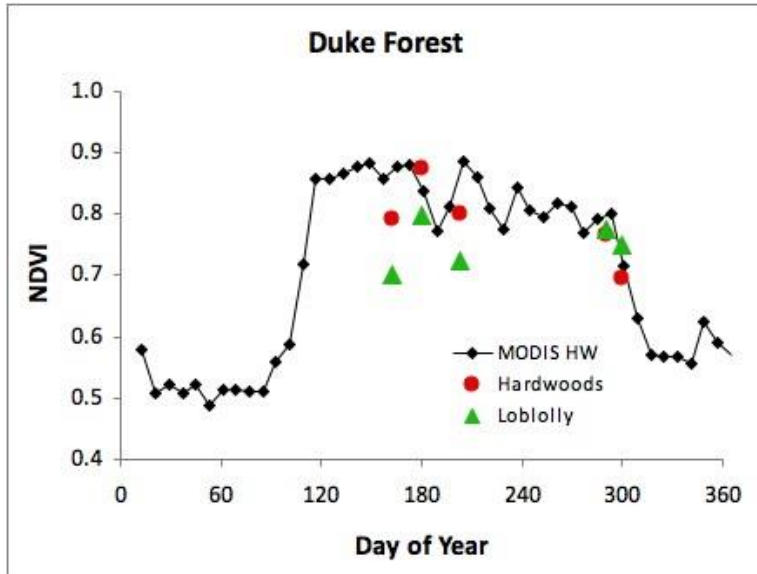
- Tallgrass Prairie

- Two towers, each n=7



# Seasonal Data

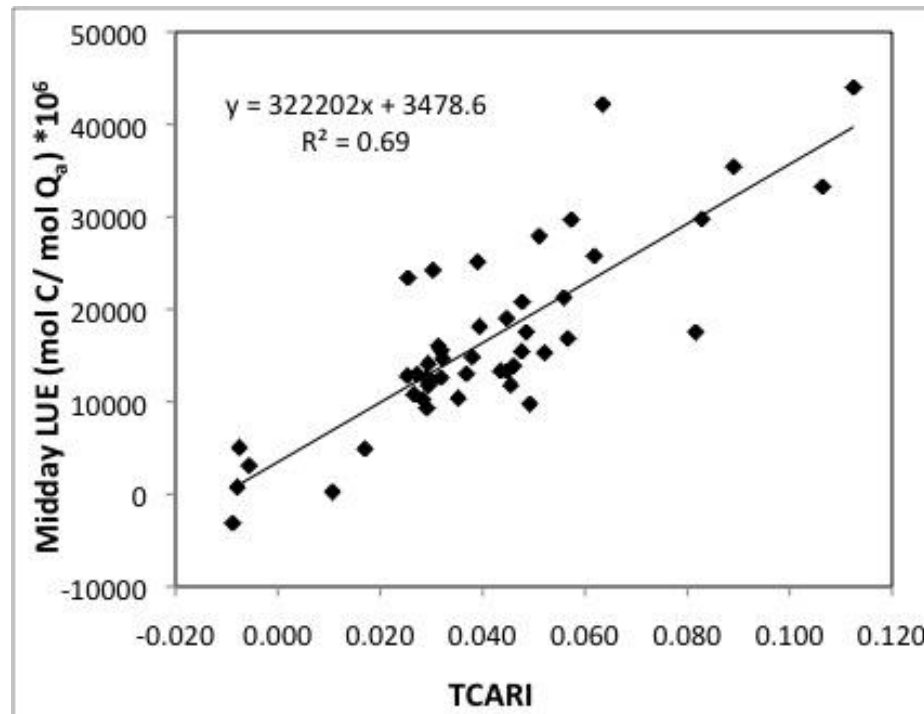
Seasonal change is described by Hyperion's repeated observations



- Black points – NDVI from MODIS N-bar
- Red and Green points – NDVI from Hyperion bands convolved to MODIS bands

# Spectral Vegetation Indices

- Calculated 101 SVIs from Hyperion surface reflectance
- Compared with midday LUE using data from all sites
  - TCARI performed best,  $R^2=0.69$
  - Provides a baseline to compare with statistical approach



Transformed Chlorophyll Absorption Ratio Index (TCARI)

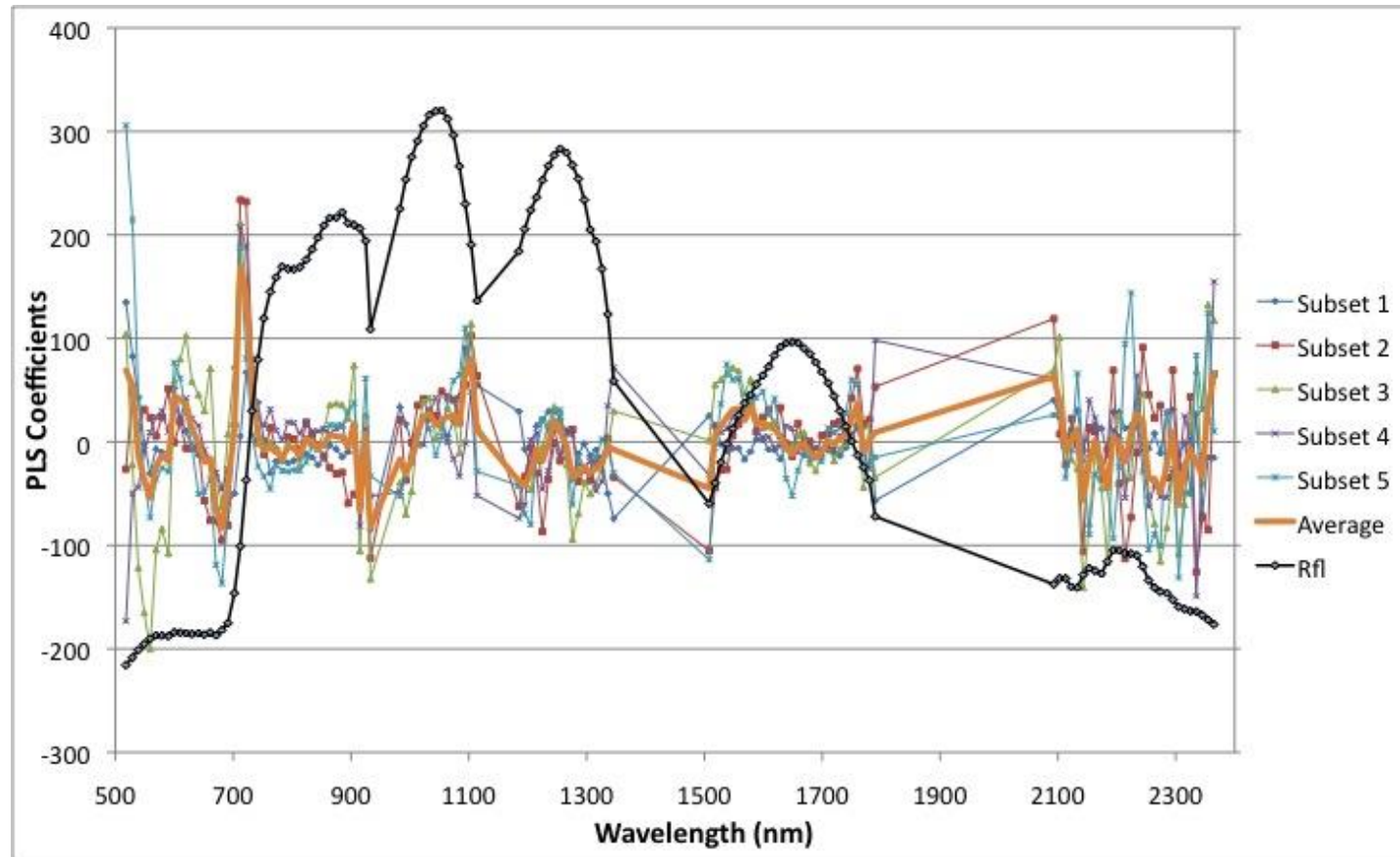
$$TCARI = 3[(R700-R670)-0.2(R700-R550)(R700/R670)]$$

Kim et al. 1994

RMSE = 5494, R = 0.83

# Partial Least Squares Regression

- PLSR uses information from all spectral bands (129 bands)
- Trained using random subsets from all sites
- Produces coefficients for every spectral band

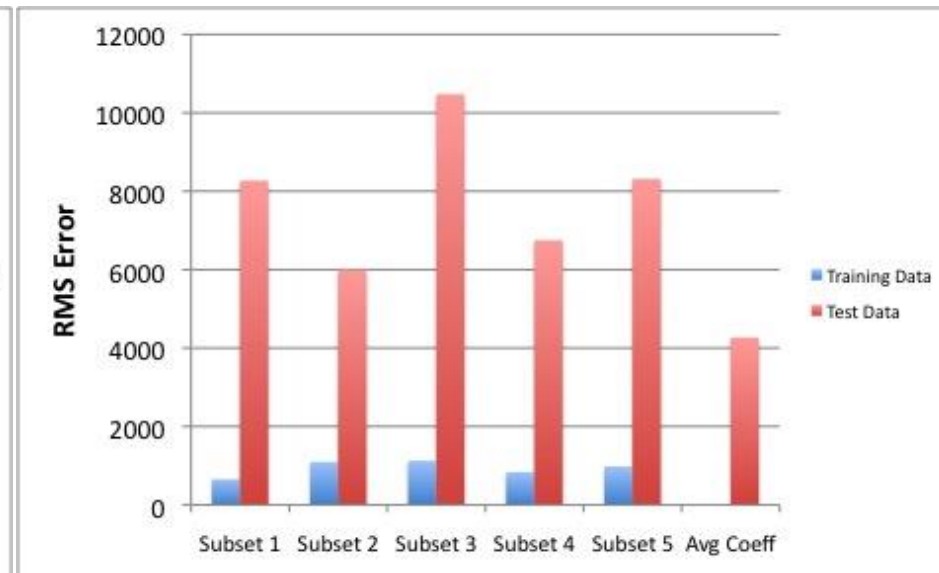
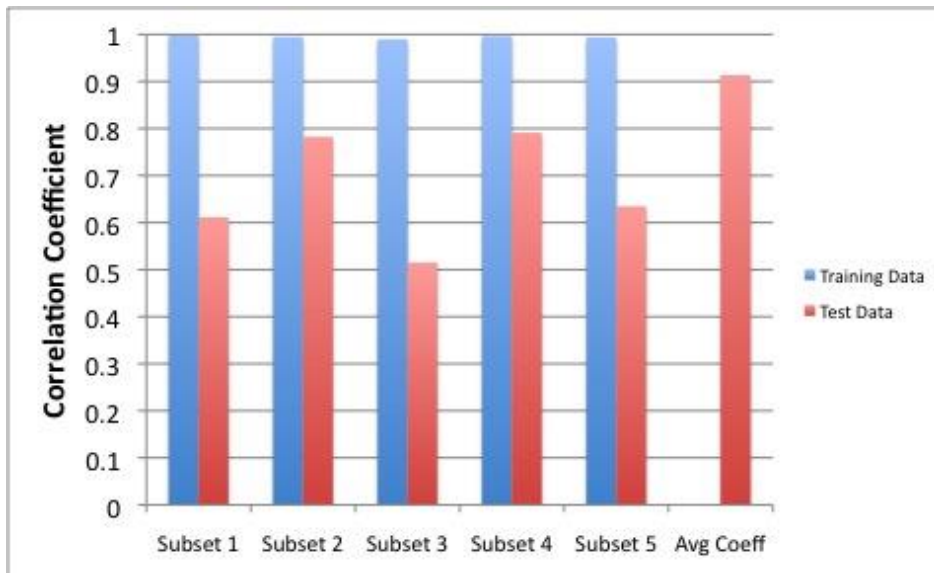


Black line is mean reflectance of all spectra



# Partial Least Squares Regression

- PLSR produces great results for the training subsets
- R for all the test subsets are less than the best SVI (TCARI R=0.83)
  - Poorer RMSE for the test subset data (TCARI RMSE = 5494)
- The average of the coefficients from all the subsets does slightly better than TSAVI



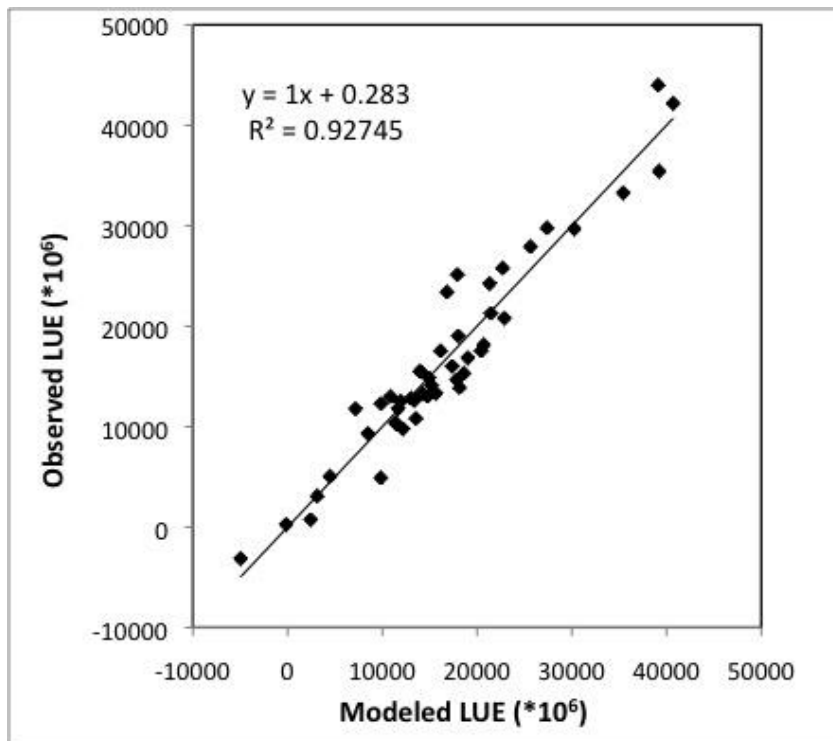
Blue Bars – PLSR applied to training data subset, n=23

Red Bars – PLSR applied to test data subset, n=24

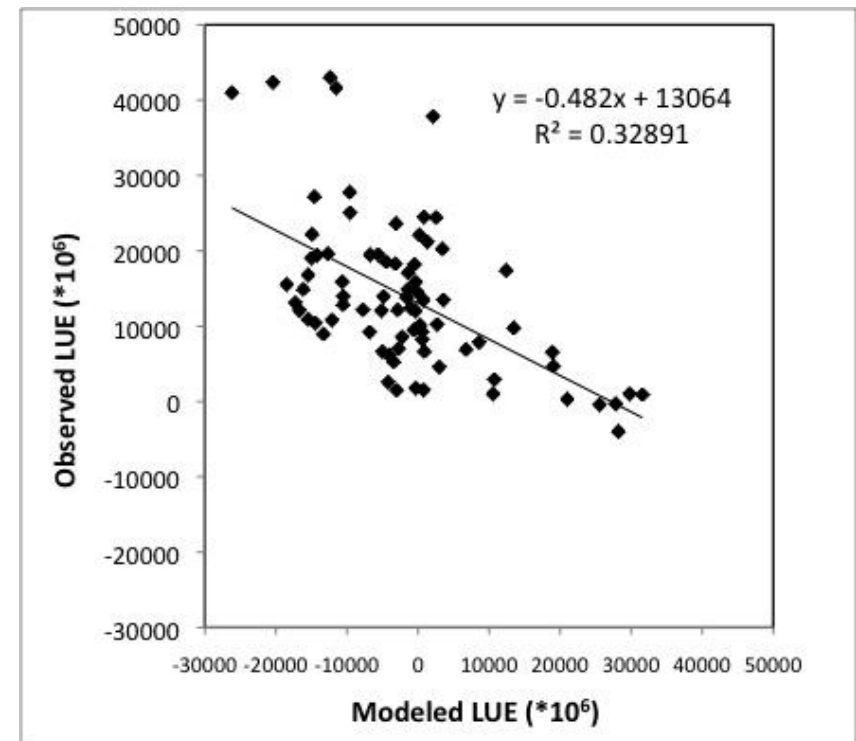
# How extendable are the PLSR results?

- Use all the data for training PLSR
- Use Multisite dataset from previous study to test
  - Multisite dataset – 33 sites, n=79, only mid-growing season observations

Training Data: Multitemporal  
Test Data: Multitemporal

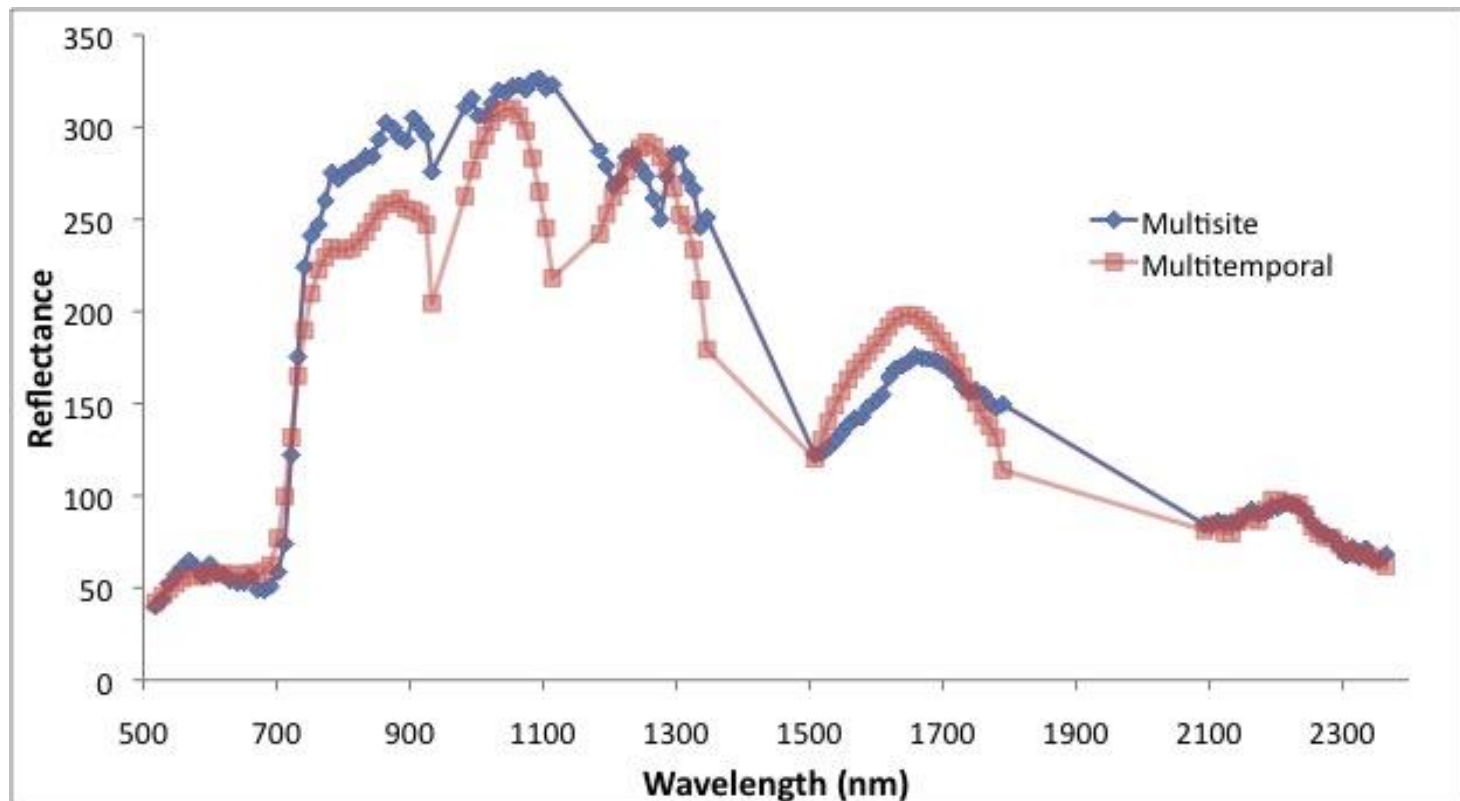


Training Data: Multitemporal  
Test Data: Multisite



# What caused the differences?

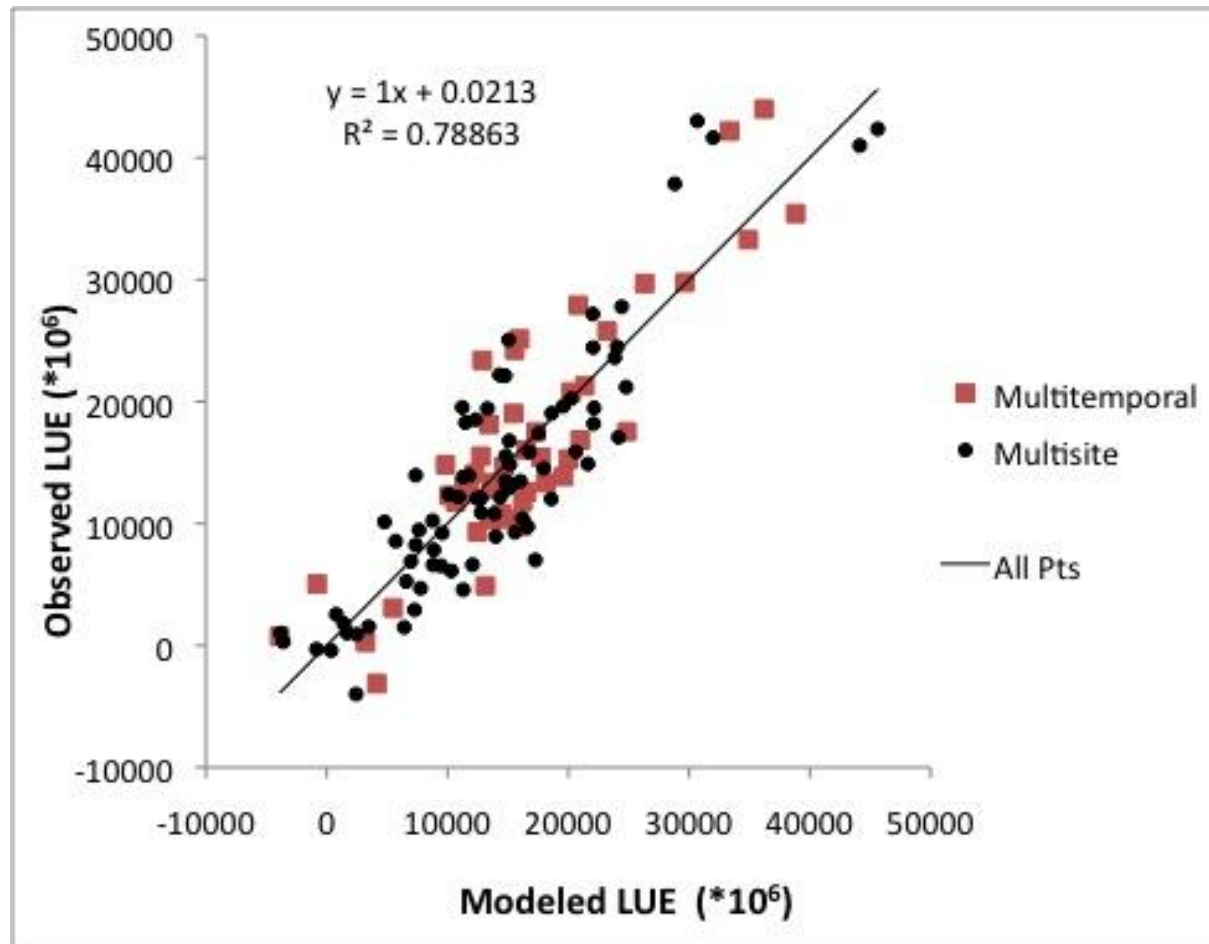
- PLSR coefficients failed because of differences in Hyperion reflectances due to atmospheric correction
  - Multisite data were processed with ATREM, Multitemporal data were processed with ACORN
  - An important consideration for spectral libraries



Average reflectance of all observations of each type

# PLSR can get reasonable results for all points combined

- Trained using all points from both Multitemporal and Multisite datasets



# Conclusions

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- A general approach for retrieval of biophysical variables without classification may yet be possible
  - Information from multiple spectral bands is required
- Statistical approaches like PLSR can be powerful tools for data analysis and product generation
  - Critically important to have good training data that represents the full range of cases
  - Differences in processing approaches may result in significant errors
- Hyperion's ability to provide multitemporal and multisite observations makes it an important tool for pre-HyspIRI algorithm development and testing