Mapping Plant Species and Plant Functional Types from the West Coast to the Gulf

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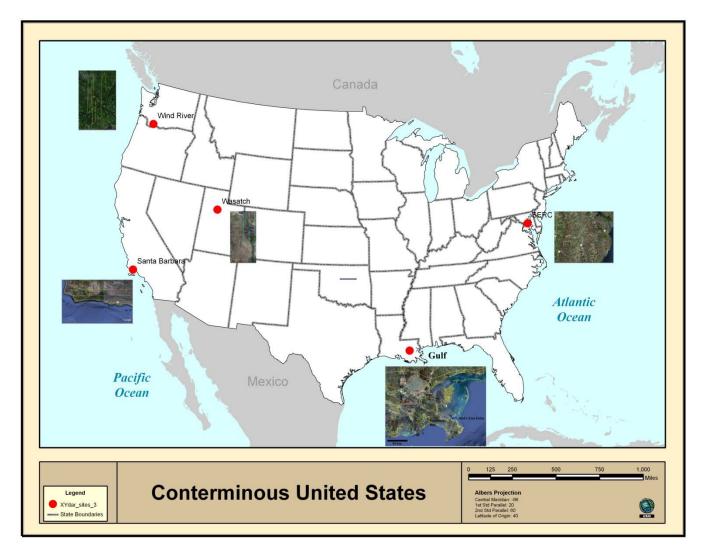
- 1. UC Santa Barbara
- 2. University of Utah
- 3. USGS Denver
- 4. UC Davis

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Research Questions

- How separable are plants at the species and plant functional type (PFT) level using imaging spectrometry?
- How does the ability to discriminate species/PFTS vary as a function of
 - Spatial resolution (4 to 60m)?
 - Spectral sampling (Broad band to imaging spectrometry)?
 - Seasonality?
- How does separability vary across multiple ecosystems?

Terrestrial Ecology Study Sites



Additional sites include Sierra Nevada and Jasper Ridge

How do you Quantify Spectral Separability?

• Spectral distance measures

- Jeffries-Matsusita
- Bhattacharyya distance

$$B = \frac{1}{8} [\mu_1 - \mu_2]^T \left[\frac{\Sigma_1 + \Sigma_2}{2} \right]^{-1} [\mu_1 - \mu_2] + \frac{1}{2} Ln \frac{\left| \frac{1}{2} [\Sigma_1 + \Sigma_2] \right|}{\sqrt{|\Sigma_1||\Sigma_2|}}$$

• Statistical

(μ - mean value | Σ - Covariance)

- t-test
- Classification
 - Least Squares Analysis of Absorption Features (MICA)
 - Linear Discriminant Analysis
 - Spectral Angle Mapper
 - Multiple Endmember Spectral Mixture Analysis
 - Extension of simple mixing model
 - Number and type vary per pixel
 - 2 em case

Selecting Optimal Endmembers for MESMA

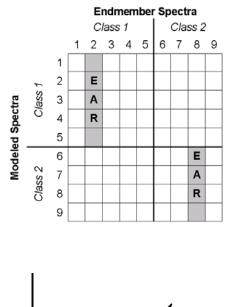
- Objective
 - Select the smallest subset of spectra that has the least confusion between classes
- Approaches
 - Count-Based Endmember Selection (COB)
 - Endmember Average RMS (EAR)

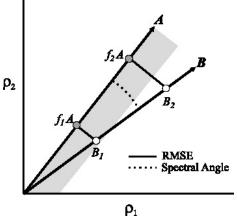
$$\text{EAR}_{A_{i},B} = \frac{\sum_{j=1}^{n} \text{RMSE}_{A_{i},B_{j}}}{1}$$

 Minimum Average Spectral Angle (MASA)

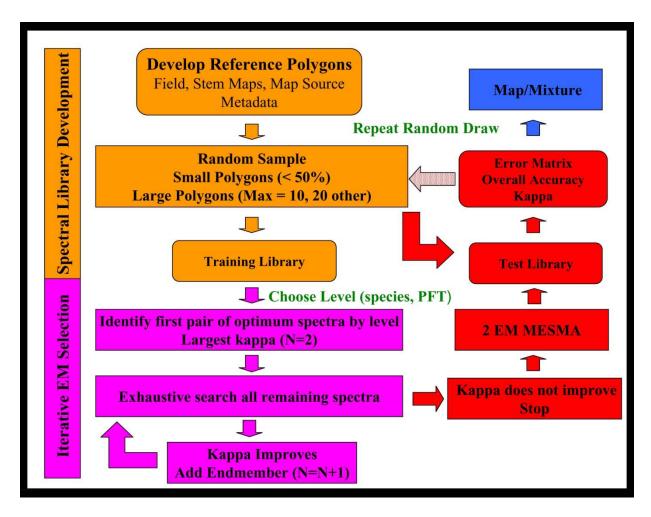
$$ilde{ heta}_{\mathcal{A}_i,\mathcal{B}} = rac{\displaystyle\sum_{j=1}^n heta_{\mathcal{A}_i,\mathcal{B}_j}}{n-1}$$

- Limitations
 - Difficult to evaluate relative merits of each approach and standardize
 - May not capture important em variability
 - Does not evaluate relative merits of individual ems or optimize accuracy

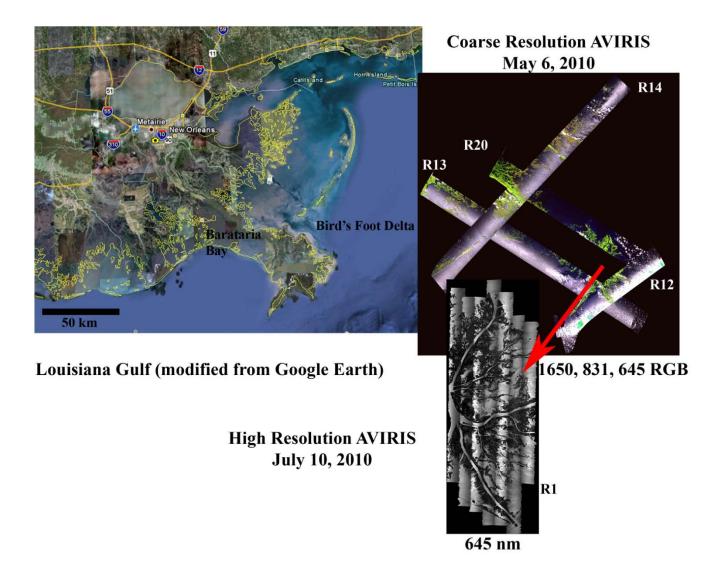




Iterative Endmember Selection and Random Selection



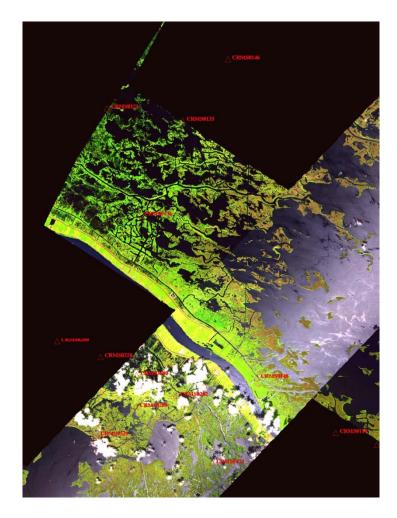
Gulf Study Site: In Detail



Building a Spectral Library: Examples from the Gulf

- Identify suitable reference data for training and validation
 - CRMS (Coastal Reference Monitoring System)
 - NWRC (National Wetland Research Center)
- Extract spectra, construct metadata, sample training and test libraries
- Select optimum spectra

Challenges: •Clouds, water, glint, tides •Limited sites •Limited species sampled



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Endmember Selection: EAR, MASA, COB

- Spectra selected from complete library
- Classification accuracy evaluated with test library

	disp	dwtr	glint	juro	mwtr	phau	spal	sppa	vilu	users
disp	4	0	0	0	0	5	14	1	0	16.67%
dwtr	0	39	0	0	0	0	0	0	0	100.00%
glint	0	0	53	0	0	0	0	0	0	100.00%
juro	0	0	0	1	0	0	40	1	0	2.38%
mwtr	0	31	0	0	48	0	0	0	0	60.76%
phau	0	0	0	0	0	80	47	8	6	56.74%
spal	0	0	0	1	0	12	178	9	2	88.12%
sppa	1	0	0	0	0	26	36	17	1	20.99%
vilu	0	0	0	0	0	0	0	0	0	0.00%
Producer	80.00%	55.71%	100.00%	50.00%	100.00%	65.04%	56.51%	47.22%	0.00%	63.54%
Kappa	0.536									
Kappa v	0.00052									

•26 spectra selected, including 1 disp (*Distichlis spicata*), 4 water, 3 glint, 1 juro (*Juncus roemerianus*), 5 phau (*Phragmites australis*), 6 spal (*Spartina alterniflora*), 3 sppa (*S. patens*) and 3 vilu (*Vigna luteola*)

•Classification accuracy is reasonable, but certain classes (juro,sppa and vilu) were poor •Two classes (disp and juro) are poorly represented

Iterative Endmember Selection

- Spectra selected from one training library
- Classification accuracy evaluated with remaining spectra (test library)

	disp	dwtr	glint	juro	mwtr	phau	spal	sppa	vilu	users
disp	0	0	0	0	0	0	0	0	0	0.00%
dwtr	0	70	0	0	0	0	0	0	0	100.00%
glint	0	0	53	0	0	0	1	0	0	98.15%
juro	0	0	0	0	0	0	0	0	0	0.00%
mwtr	0	0	0	0	48	0	0	0	0	100.00%
phau	0	0	0	0	0	121	26	9	6	74.69%
spal	5	0	0	2	0	15	303	20	3	87.07%
sppa	0	0	0	0	0	4	6	11	0	52.38%
vilu	0	0	0	0	0	1	1	8	7	41.18%
Producers	0.00%	100.00%	100.00%	0.00%	100.00%	85.82%	89.91%	22.92%	43.75%	85.14%
Kappa	0.79									
Kappa v	0.000336									

- •*31 spectra selected, including 3 water, 2 glint, 6 phau, 9 spal, 5 sppa and 6 vilu
- •Classification accuracy was significantly higher than EMC
- •Two classes (disp and juro) were not selected because of low sample numbers

•Reduced errors of commission

Wetland Spectra: Vol. I

- Water spectra included dark water, muddy water and glint
 - This list was not comprehensive
- *Phragmites* is defined by a "classic" spectrum varying primarily in brightness
 - Some mixed water spectra occurred



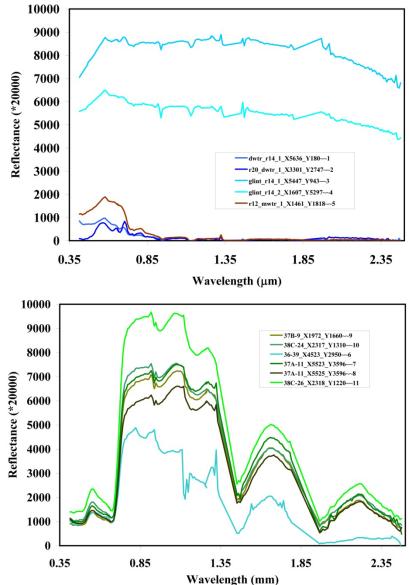


Photo source:http://plants.usda.gov/java/profile?symbol=PHAU7&photoID=phau7_002_avp.tif

Wetland Spectra: Vol. II

• *Spartina alterniflora* is highly variable, generally dark due to structure

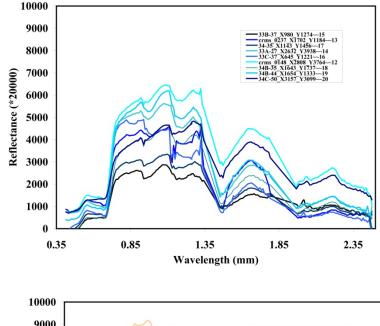


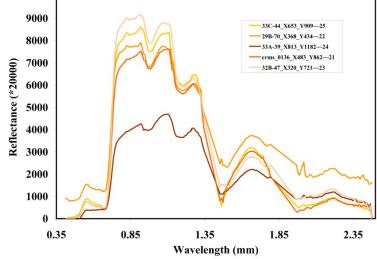
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Spartina patens is less variable

Spartina patens is less variab and brighter





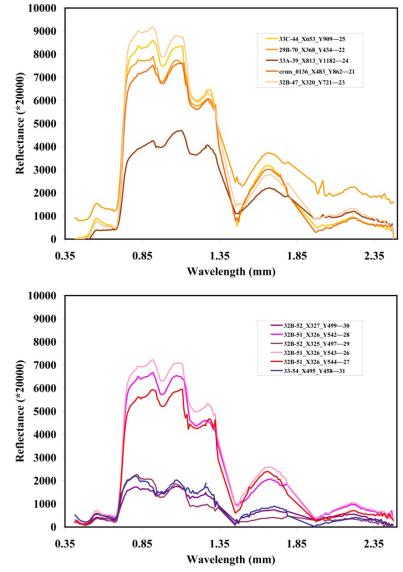


Source: http://www.google.com/imgres?imgurl=http://siera104.com/images/bio/ecology/saltmeadow.jpg

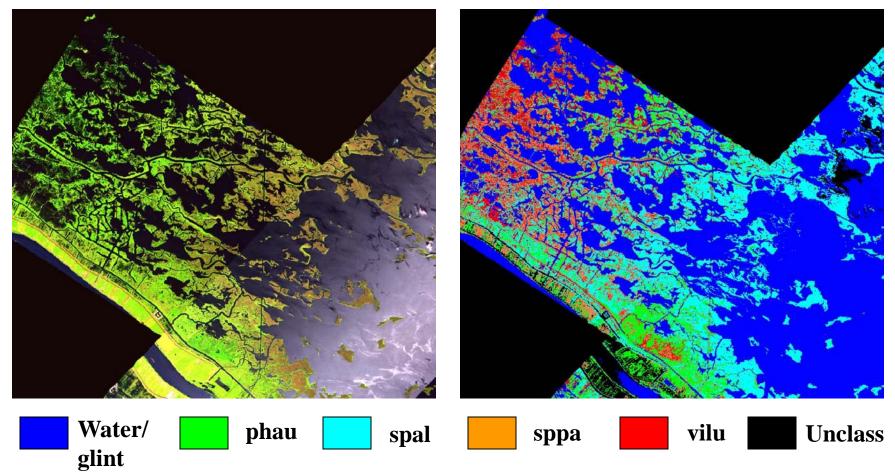
Wetland Spectra: Vol. III

- Vigna luteola is defined by a bimodal reflectance between bright (unflooded) and dark (flooded?) spectra
 - sppa is included for comparison



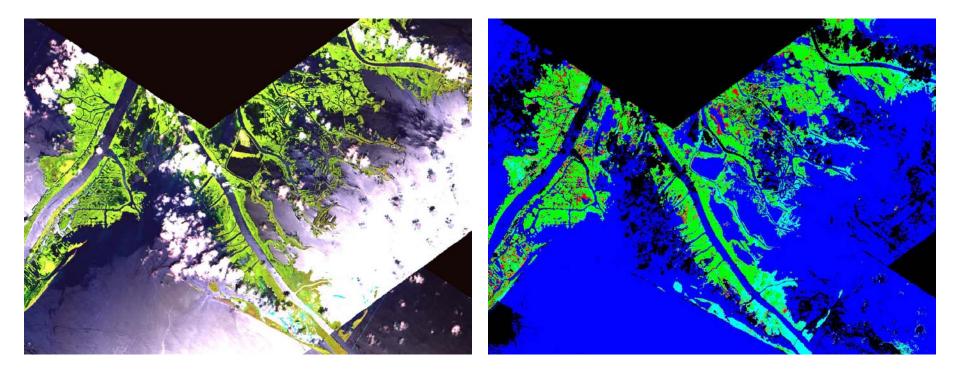


Mapping Wetland Dominants



- Vegetation mapped cleanly across scene boundaries
- Accuracy appears higher than reported using the test library due to mixed species in the NWRC sites

Mapping Wetland Dominants





- Vegetation mapped cleanly across scene boundaries
- Phragmites dominates farther south along the delta

Wind River

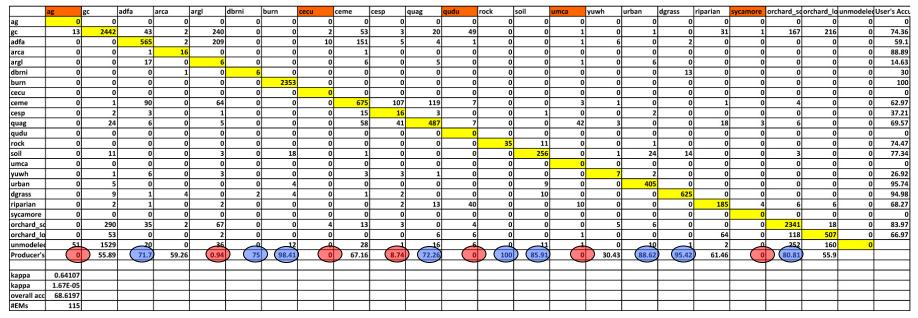
- Species-level accuracy of 72.7% for 10 species and 63 endmembers
- PFT accuracy of 96.8% for 4 PFTs
 - Vertical height information would remove ambiguity between herbs and broadleaf plants

R. Stran			
Contraction of the second			
			unclassified
		KA A	deciduous herb
			annual grass
			rock/soil
	Research State		evergreen needleleaf
			deciduous broadleaf
			N
			Ą
State and a			
			Kilometers

	broadleaf	grass	herb	needleleaf	soil	unmodeled	users_acc
broadleaf	2286	0	18	416	0	0	84.0441
grass	0	3475	1	5	1	0	99.799
herb	17	38	22	51	0	0	17.1875
needleleaf	86	60	4	16816	0	0	99.1159
soil	0	9	0	0	39	0	81.25
unmodeled	0	28	0	7	0	0	
prod_acc	95.68857	96.26039	48.88889	97.23041	97.5	0	
kappa		0.92599					
overall accuracy		96.8305					

Santa Barbara Front Range

- 13 species, 9 other categories (i.e., soil, rock, orchards) totaling 115 ems
- Species accuracy of 68.6%
- PFT level (8 PFT + 6 other), 103 ems, 81% accuracy

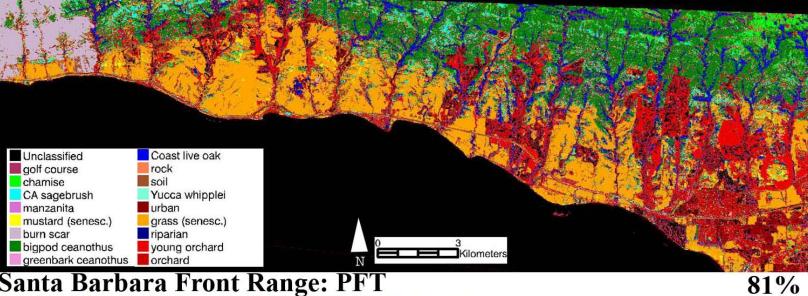


- Highly accurate (>70%) classes include adfa, dbrni, burn, quag, rock, soil, urban, dead grass, orchard+soil)
- Intermediate (50-70%) include golf courses, arca, ceme, riparian, except argl &cesp)

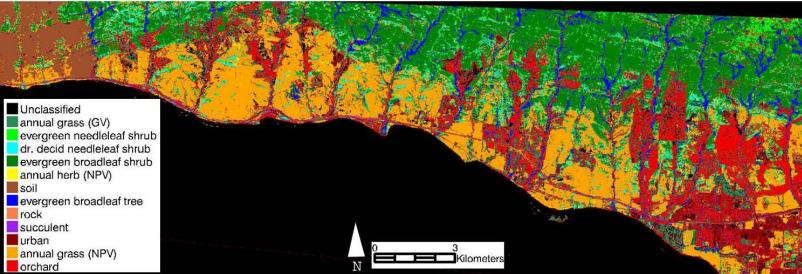
Santa Barbara Front Range

Santa Barbara Front Range: Species

68.6%



Santa Barbara Front Range: PFT



* High Accuracy extends to the northern line with opposite viewing geometry

Other Experiments with Iterative Endmember Selection

- Impact of degraded spatial resolution (4-60 m)
 - On-going, all sites: See Dennison
- Impact of degraded spectral resolution (native resolution)

Kappa Statistic

– On-going		AVIRIS	IKONOS	MODIS	SPOT5	TM5
	SERC	0.37	0.088	0.23	-0.092	-0.067
Keely Roth	SBFR species	0.60	0.31	0.49	0.34	0.39
v	SBFR PFTs	0.63	0.52	0.56	0.45	0.51
	WR species	0.62	0.28	0.39	0.31	0.36
	WR PFTs	0.93	0.45	0.84	0.82	0.77

• Impact of random sampling

- **100 runs:**
 - Accuracy varies substantially between models
 - Do you choose the best of 100 or build an ensemble of models?

On-going Research in the Gulf

- Improve spectral library to include missing species
 - Juncus roemerianus, Distichlis spicata, Mangroves
- Export analysis to July Twin Otter data sets
 - Understory glint appears to have drastically changed the spectral shape of some wetlands
 - Differences in tidal heights may have modified NIR reflectance
- Expand to three+ endmember models to map senescence and oil coated vegetation
- Calculate additional stress measures
- Image oil impacted vegetation

Questions?