GEO 827: Hyperspectral RS and Land Surface Model Benchmarking

November 10 & 12, 2015

Kyla Dahlin

Assistant Professor, Geography Department

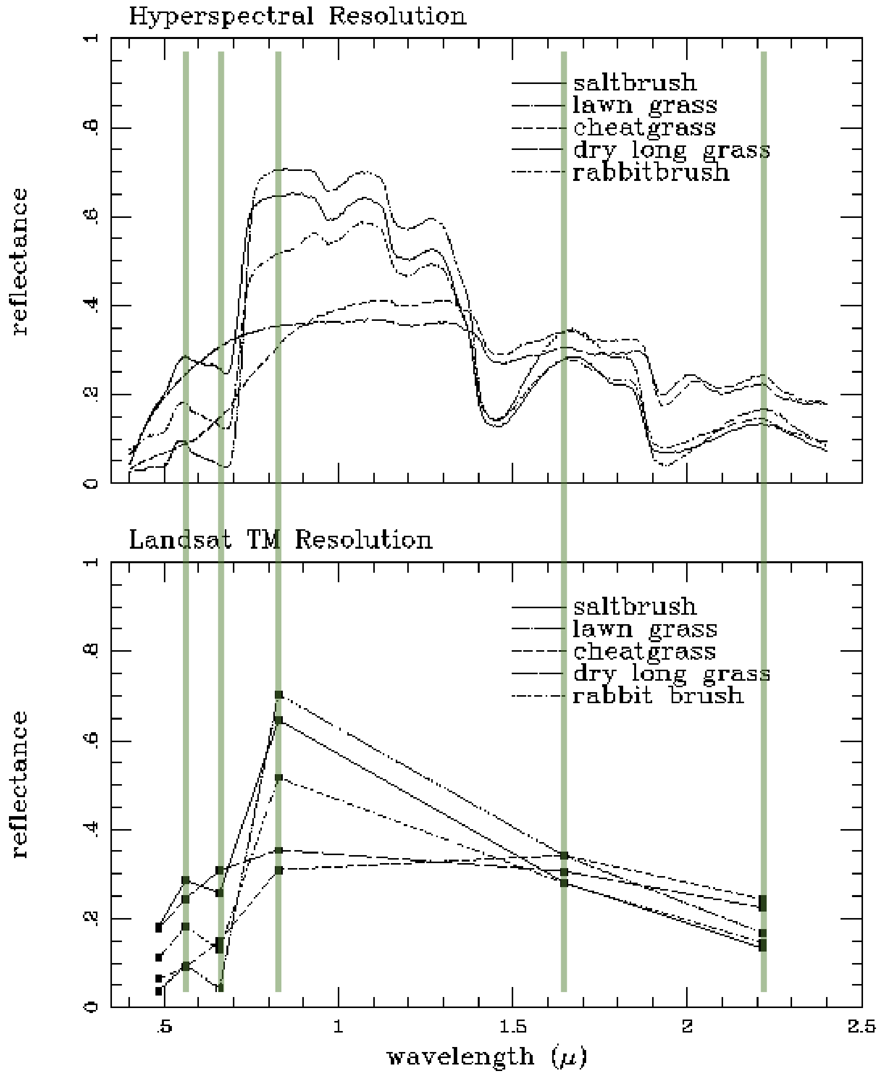
Outline for the next 2 days

- Intro to Kyla
- Intro to Hyperspectral RS
- Project examples
- Lab – exploring imaging spectroscopy in ERDAS
- Intro to Land Surface Models & Benchmarking
- Project example
- Lab – simple climate envelope modeling in R

Hyperspectral RS / Imaging Spectroscopy

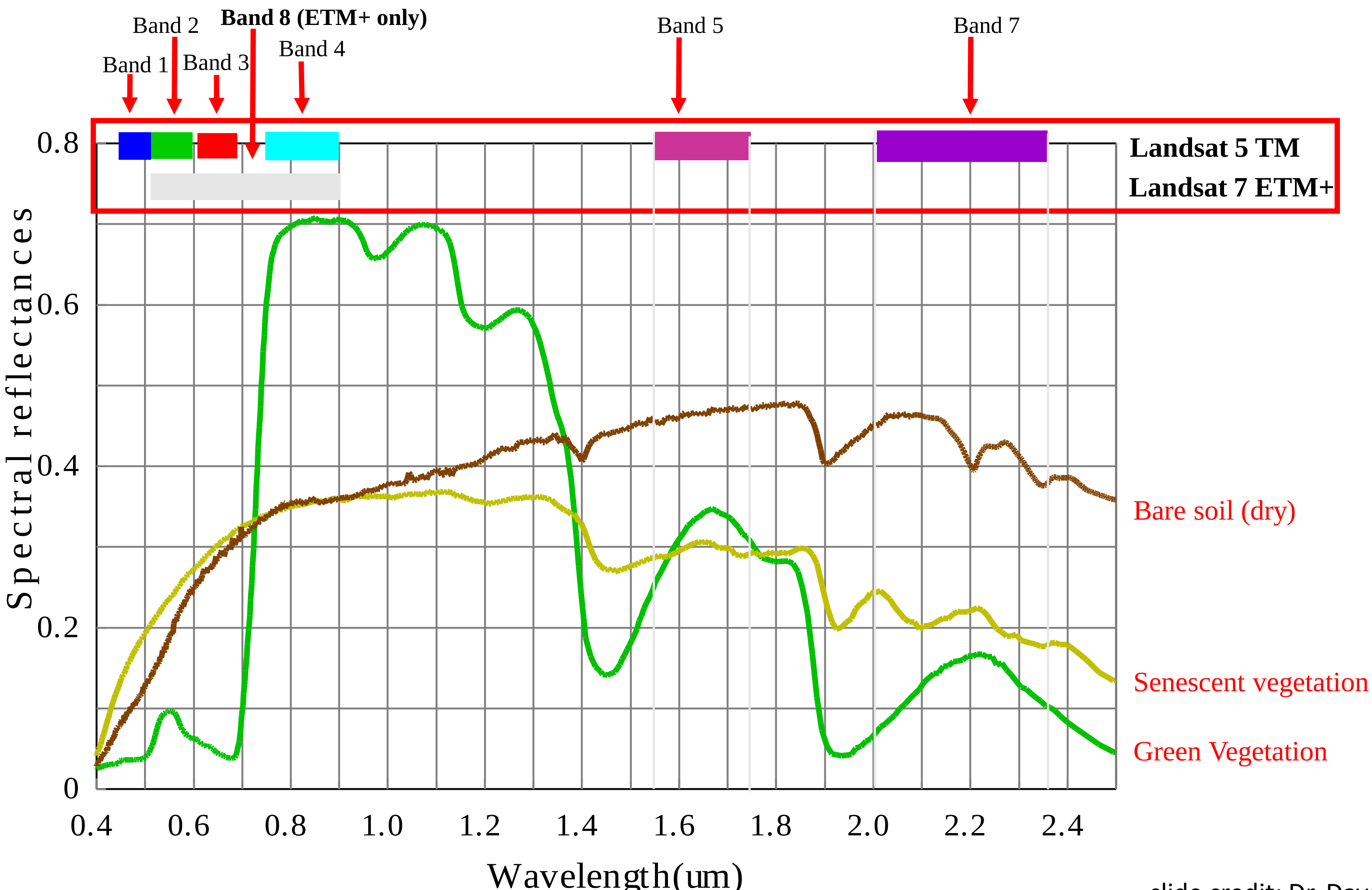
- Mean the same thing
- Measure reflected light from (typically) ~350 – 2500 nm in NARROW (5 to 10 nm) bands
- Therefore 150 – 500 bands per image
- **Read** Ustin et al 2004. Using imaging spectroscopy to study ecosystem processes and properties. *BioScience* 54(6): 523-534.

Hyperspectral RS / Imaging Spectroscopy



http://www.ece.rice.edu/~erzsebet/AVIRIS-TM-veg.html

Hyperspectral RS / Imaging Spectroscopy vs LandSat 5 & 7

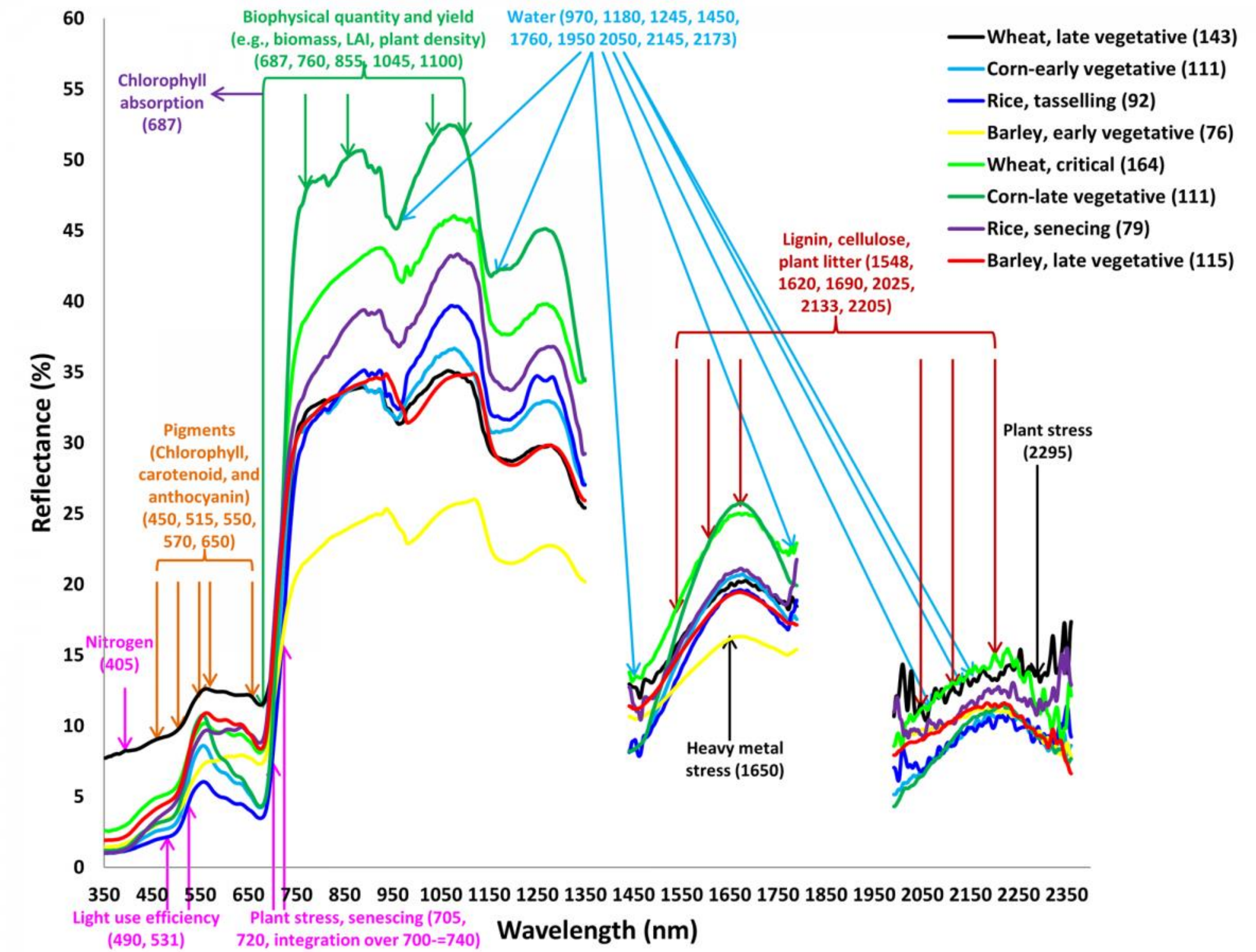


slide credit: Dr. Dave Lusch

Hyperspectral RS / Imaging Spectroscopy

- So it’s not just about the # of bands
- It’s also about their width (broad vs narrow band sensors)
- In the lab…

Hyperspectral RS / Imaging Spectroscopy



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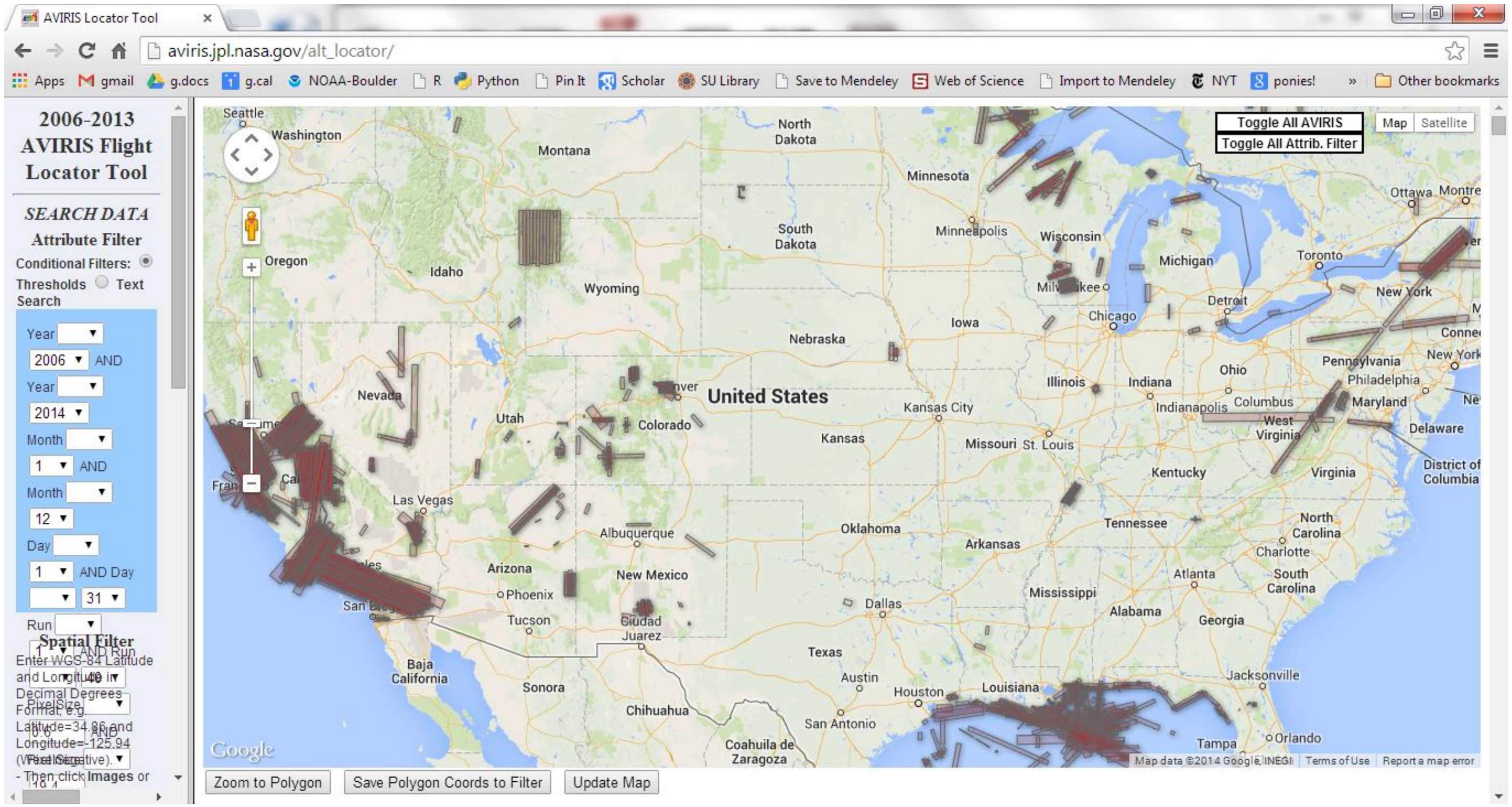
Thenkabail et al 2013; eros.usgs.gov

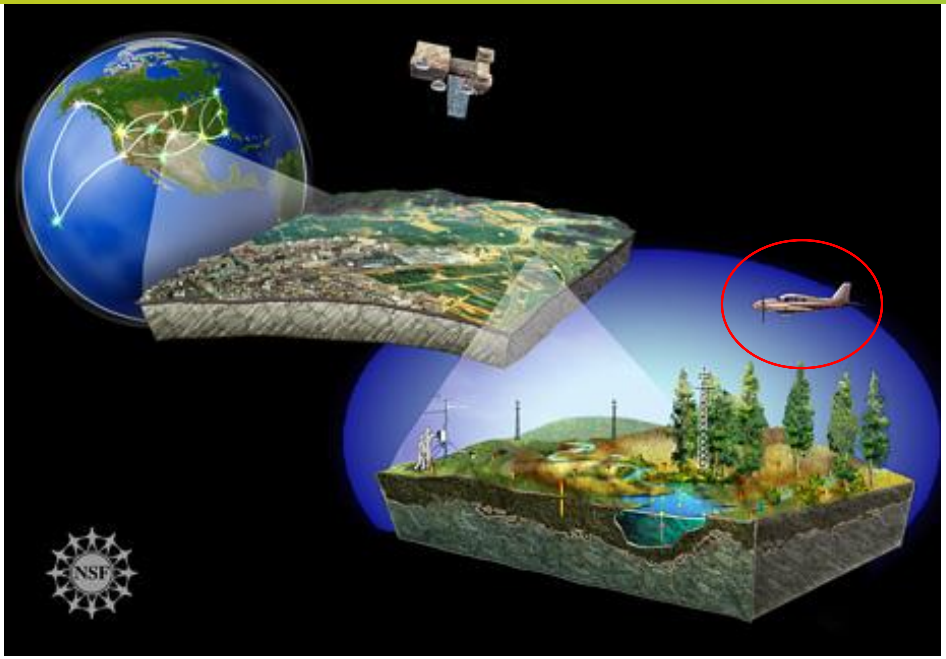
Hyperspectral RS / Imaging Spectroscopy

- Where does data come from?



Hyperspectral RS / Imaging Spectroscopy

- Where does data come from?



neoninc.org/science-design/collection-methods/airborne-remote-sensing

Hyperspectral RS / Imaging Spectroscopy

- Where does data come from?

eo1.gsfc.nasa.gov

Hyperspectral RS / Imaging Spectroscopy

- Where will data come from?

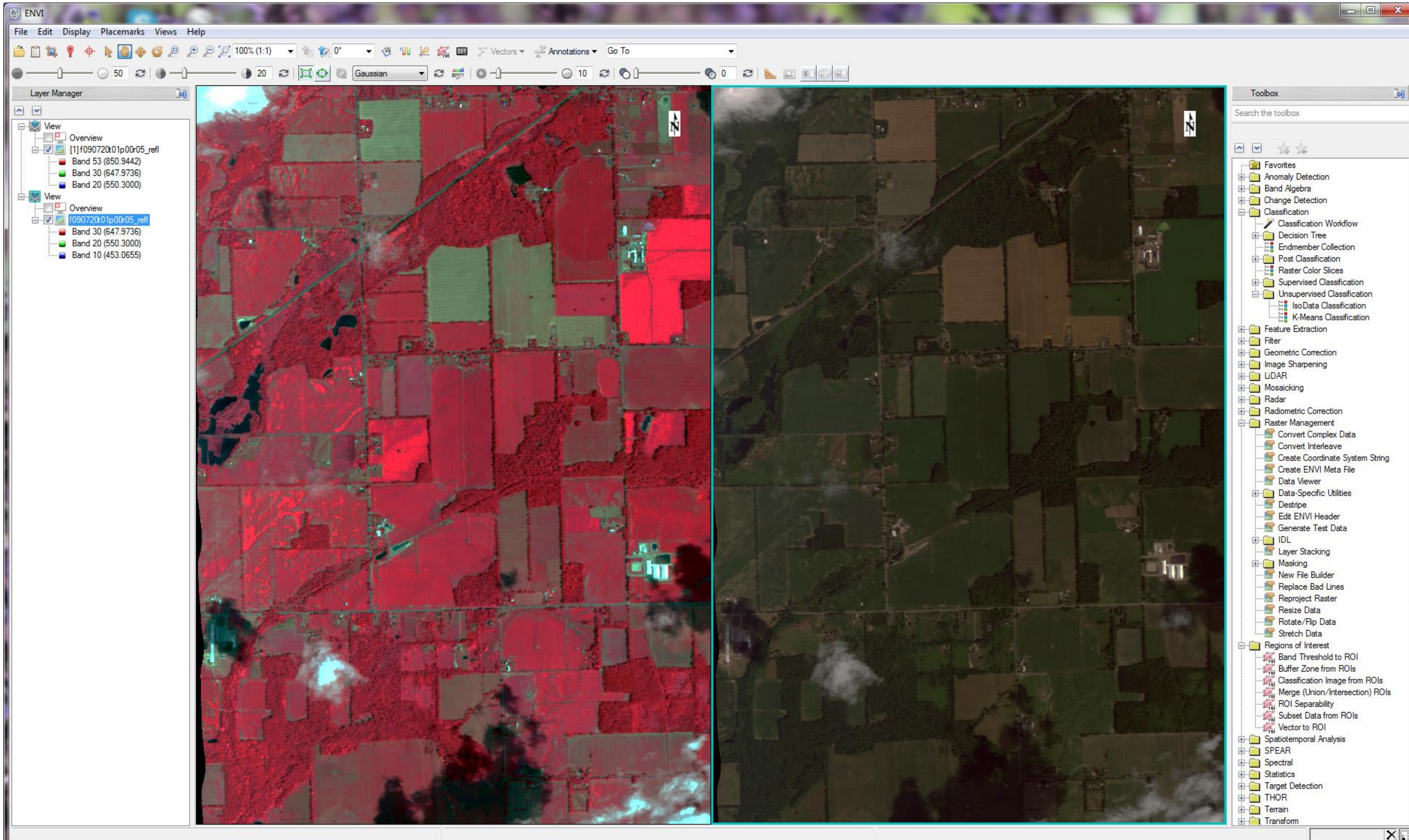
hyspiri.jpl.nasa.gov

Multiple Endmember Spectral Mixture Analysis (MESMA)

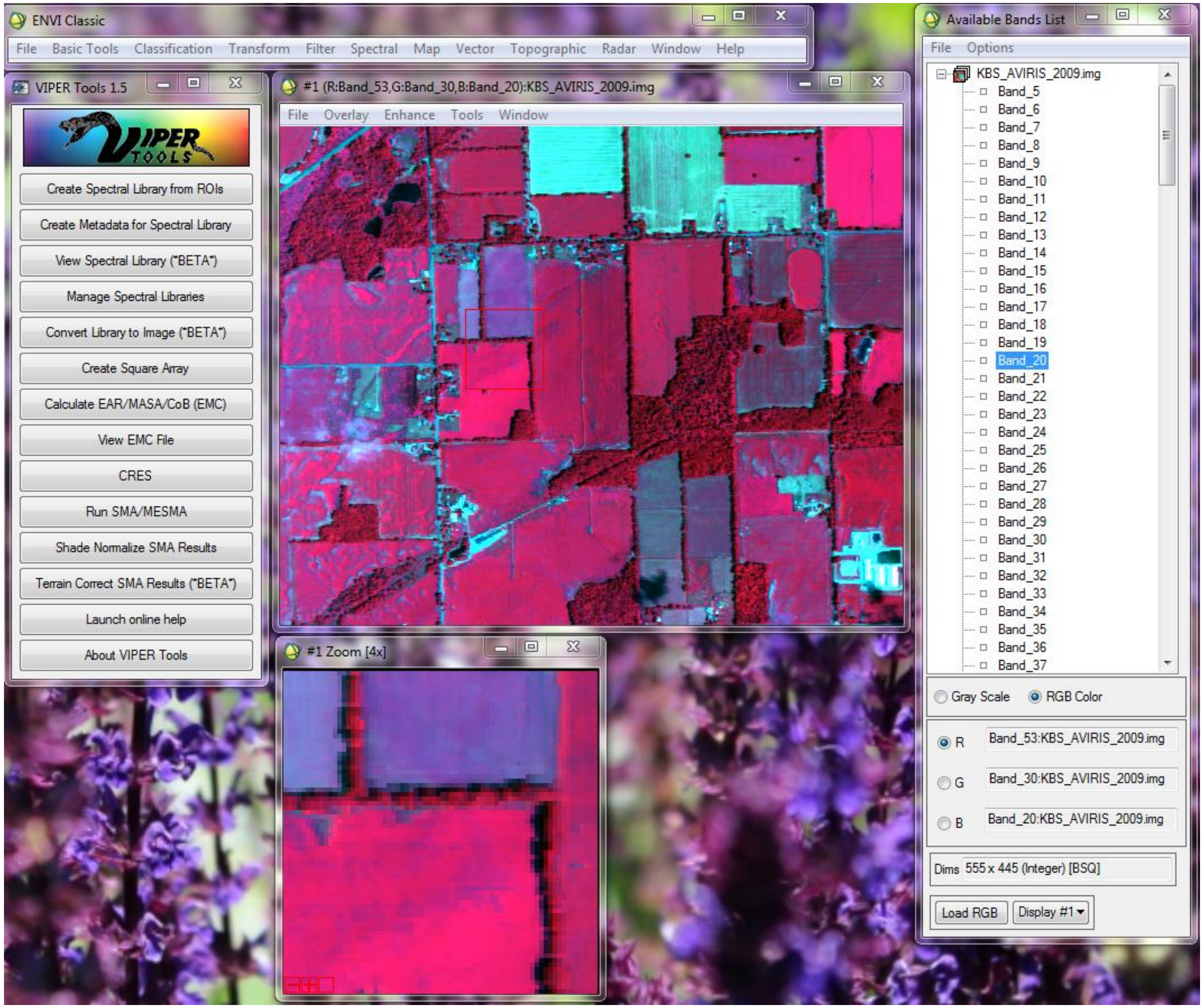
see Roberts et al 1998. Mapping chaparral in the Santa Monica Mountains using multiple endmember spectral mixture models. *Remote Sensing of Environment*. 65(3): 267-279.

- SMA is used to distinguish GV/NPV/soil.
- MESMA is a more complex version of the same ideas.
- More (image derived) endmembers.
- Multiple endmembers per target.

Multiple Endmember Spectral Mixture Analysis (MESMA) in ENVI (not)



Multiple Endmember Spectral Mixture Analysis (MESMA) in ENVI Classic



vipertools.org

Multiple Endmember Spectral Mixture Analysis (MESMA) in ENVI Classic

- Recent work:

Remote Sensing of Environment 167 (2015) 121–134

ELSEVIER

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

A multi-temporal spectral library approach for mapping vegetation species across spatial and temporal phenological gradients

CrossMark

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ABSTRACT

Variability in spectral reflectance due to spatial and temporal gradients in vegetation phenology presents issues for accurate vegetation classification. Phenological variability through space and over time can result in misclassification when spectra from non-representative areas or times are used as training data. Vegetation classification at the species level could benefit from introducing phenological information to spectral libraries, but utilization of this information across multiple dates of imagery will require new approaches to building spectral libraries and to classification. This paper explores an automated method for selecting a single multi-temporal spectral library that can be used to classify vegetation species across multiple dates within an image time series. Iterative Endmember Selection (IES) was used to select spectra from Airborne Visible Infrared Imaging Spectrometer (AVIRIS) data acquired on five dates in the same year. IES selected spectra to maximize species classification ac-

http://www.sciencedirect.com/science/article/pii/S0034425715300055

Plant species mapping using integrated airborne LiDAR & hyperspectral imagery across multiple functional groups

Project Background:

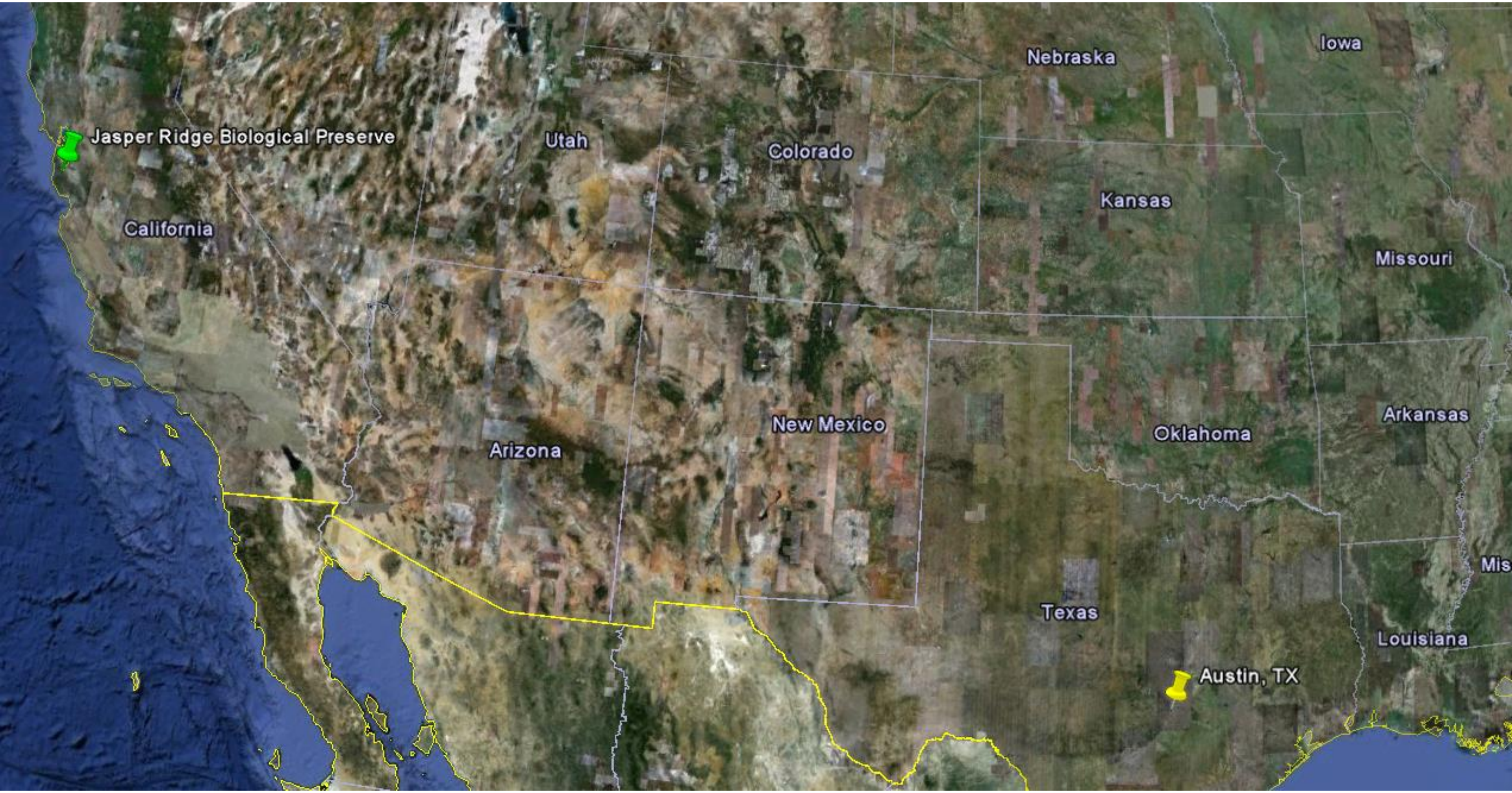
- The Carnegie Airborne Observatory (CAO) *Beta* system integrates the CAO lidar with the hyperspectral sensor AVIRIS.
- AVIRIS = 380 – 2510 nm in 10 nm bands
- Flown over Jasper Ridge Biological Preserve (JRBP) in August, 2007.
- Pixels = 2.7 x 2.7 m (= almost 9')
- The Carnegie Airborne Observatory is made possible by the Avatar Alliance Foundation, Grantham Foundation for the Protection of the Environment, John D. and Catherine T. MacArthur Foundation, Gordon and Betty Moore Foundation, W. M. Keck Foundation, Margaret A. Cargill Foundation, Mary Anne Nyburg Baker and G. Leonard Baker Jr., and William R. Hearst III.

Plant species mapping using integrated airborne LiDAR & hyperspectral imagery across multiple functional groups

Project Objectives:

- Develop a method of mapping individual plant species that capitalizes on our combination of lidar and hyperspectral data.
- Produce maps that are accurate enough to be useful to managers and to ask theoretical questions about ecosystem assembly.
- JRBP = method testing
- **The Punchline? Best TSS = 0.29**

Where?



GoogleEarth

Where?

GoogleEarth

Species Mapping Project

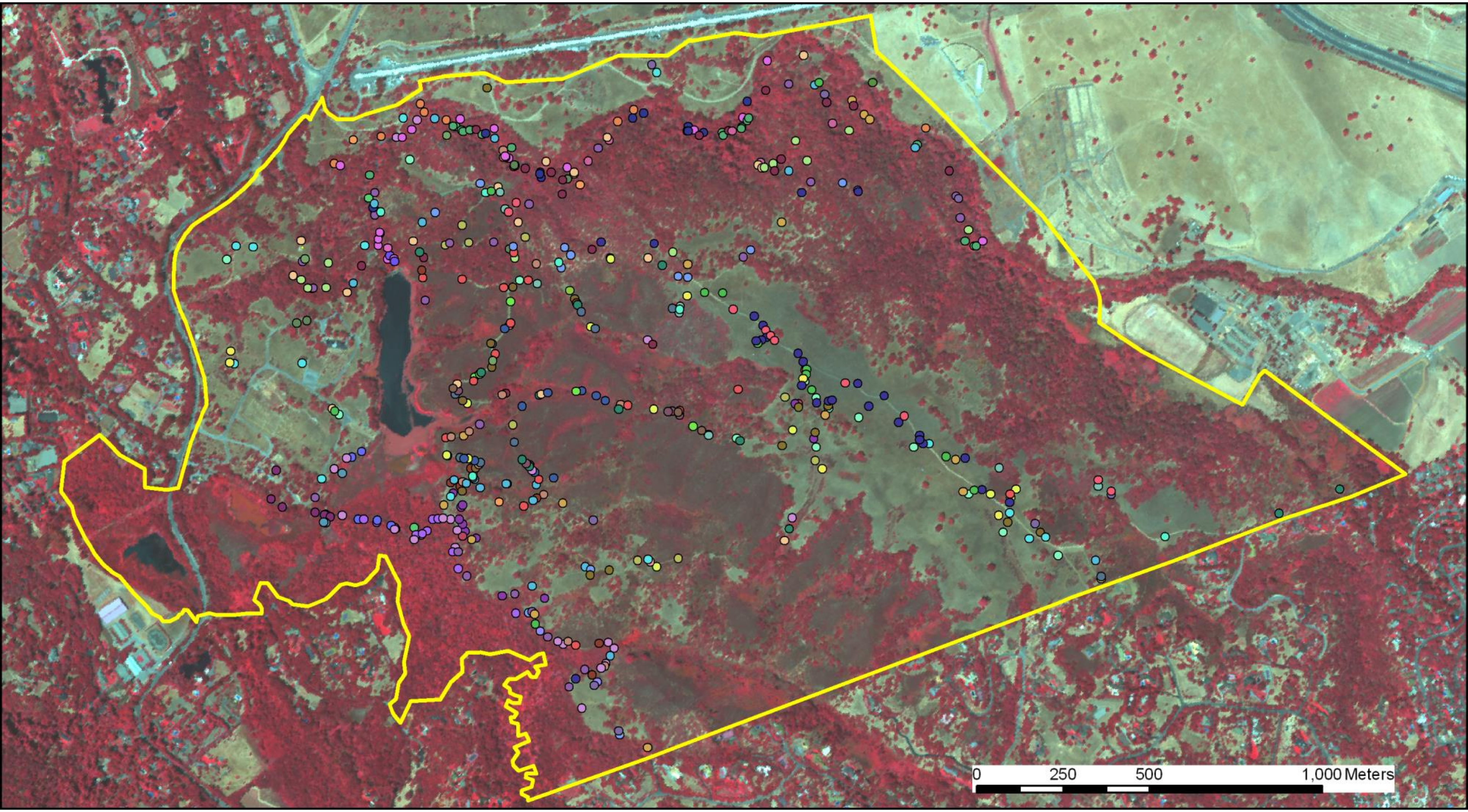
Target Species List: **38 species / types**

Species	**Common name**
Acacia sp.	Acacia
Acer macrophyllum	Big-leaf maple
Adenostoma fasciculatum	chemise
Aesculus californica	buckeye
Alnus rhombifolia	red alder
Arbutus menziesii	madrone
Artemisia californica	sagebrush
Baccharis pilularis	coyotebrush
Ceanothus cuneatus	buck brush
Ceanothus oliganthus	jim brush
Centaurea solstitialis	Yellow-star thistle
Cercocarpus betuloides	mountain mahogany
Eriodictyon californicum	yerba santa
Heteromeles arbutifolia	toyon
Holodiscus discolor	oceanspray
Juglans californica	walnut
Lepechinia calycina	pitchersage
Mimulus aurantiacus	sticky monkeyflower
Pinus radiata	Monterey pine
Prunus ilicifolia	holly-leaved cherry
Pseudotsuga menziesii	Douglas-fir
Quercus agrifolia	coast live oak
Quercus douglasii	blue oak
Quercus durata	leather oak
Quercus kelloggii	black oak
Quercus lobata	white oak
Rhamnus californica	coffeeberry
Rhamnus crocea	red buckthorn
Salix lasiolepis	arroyo willow
Salix lucida	silverleaf willow
Salix exigua	shining willow
Sambucus mexicana	Elderberry
Schoenoplectus acutus	tule
Sequoia sempervirens	coast redwood
Toxicodendron diversilobum	poison oak
Typha latifolia	cattails
Umbellularia californica	bay laurel

NON SPECIES	
Wood	soil – greenstone
grass (dry)	soil – serpentine
grass (wet)	soil – sandstone
bunch grasses	water
serpentine grasses	algae

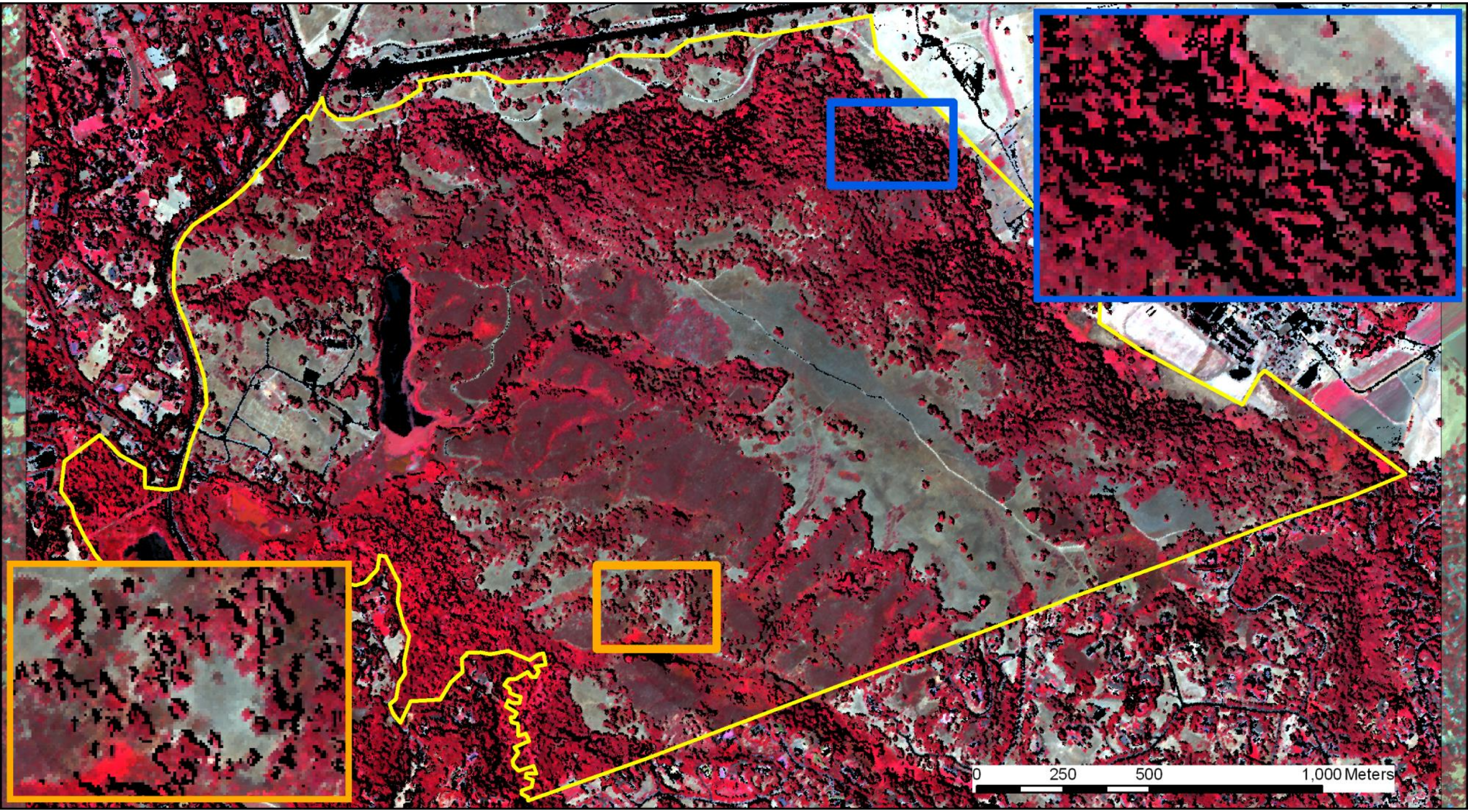
Species Mapping Project

Field Work for Endmember Selection



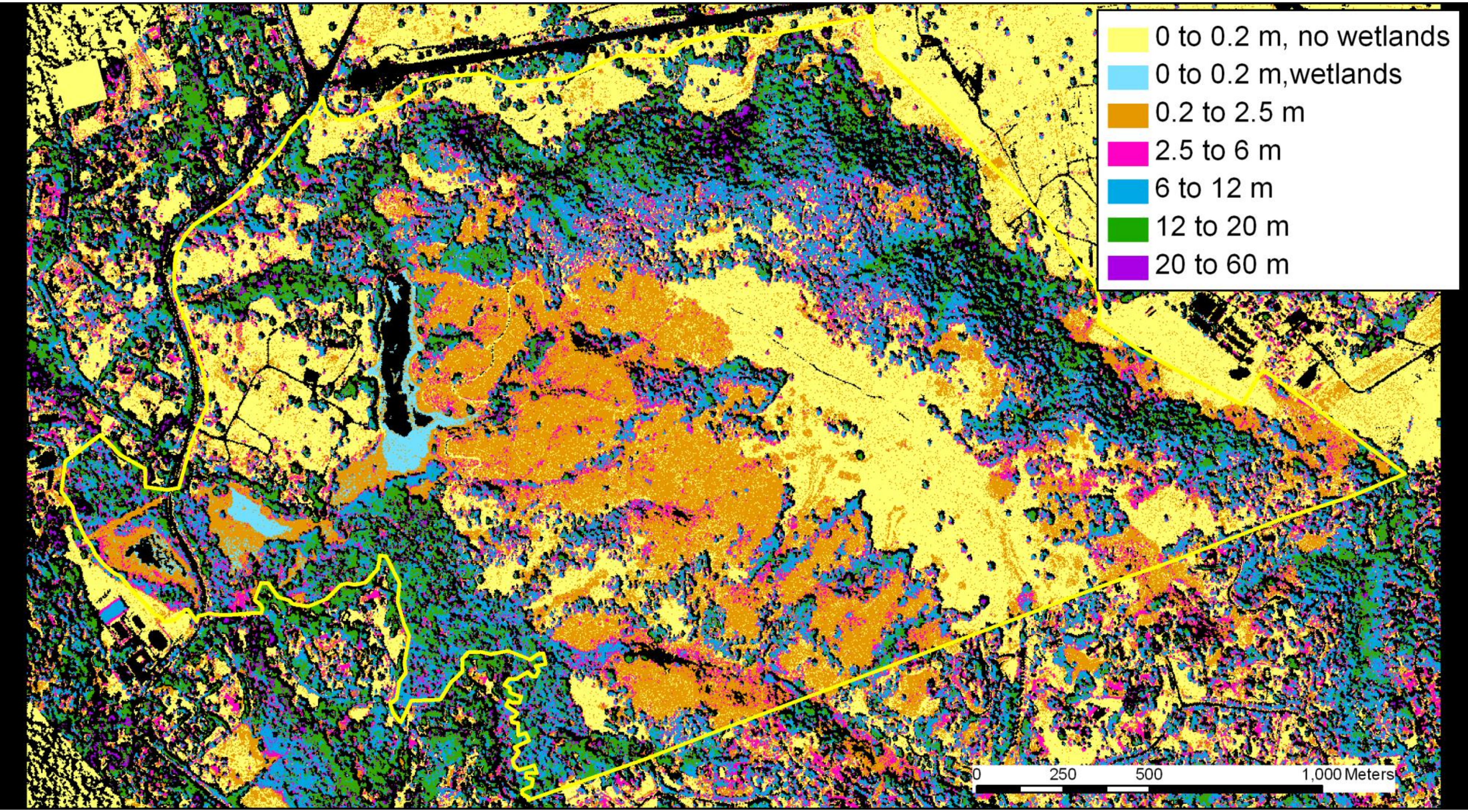
Species Mapping Project

Remove pixels based on NDVI, plane viewing angle, and canopy slope



Species Mapping Project

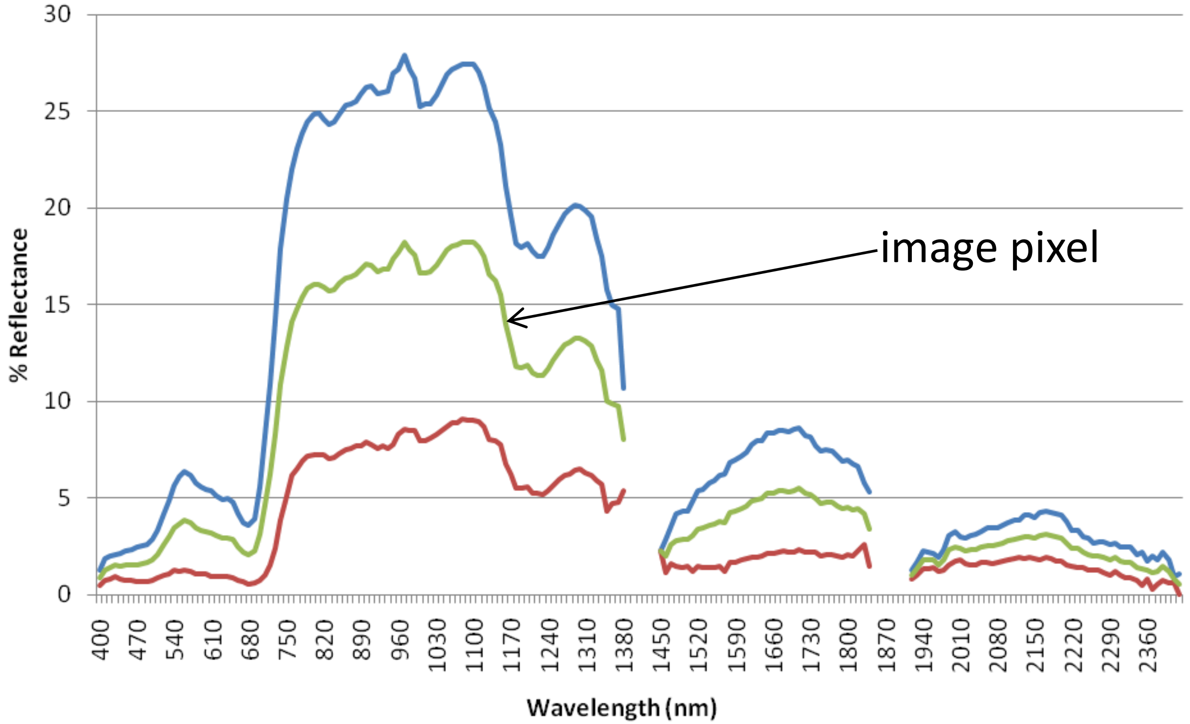
Separate the remaining data into 7 height classes



Species Mapping Project

Multiple Endmember Spectral Mixture Analysis

(Roberts *et al* 1998)



Species Mapping Project

Multiple Endmember Spectral Mixture Analysis

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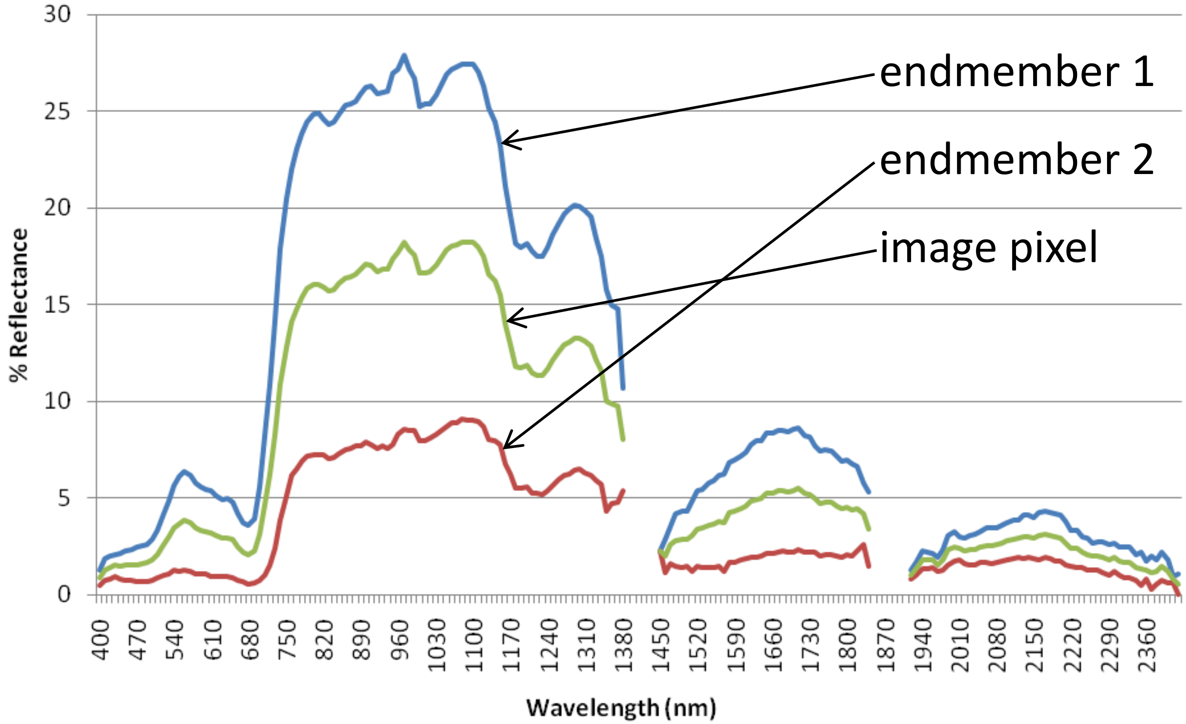
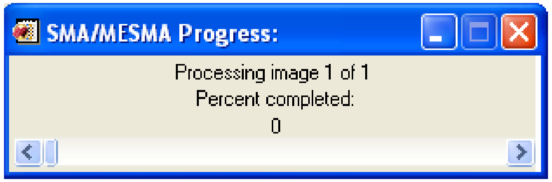


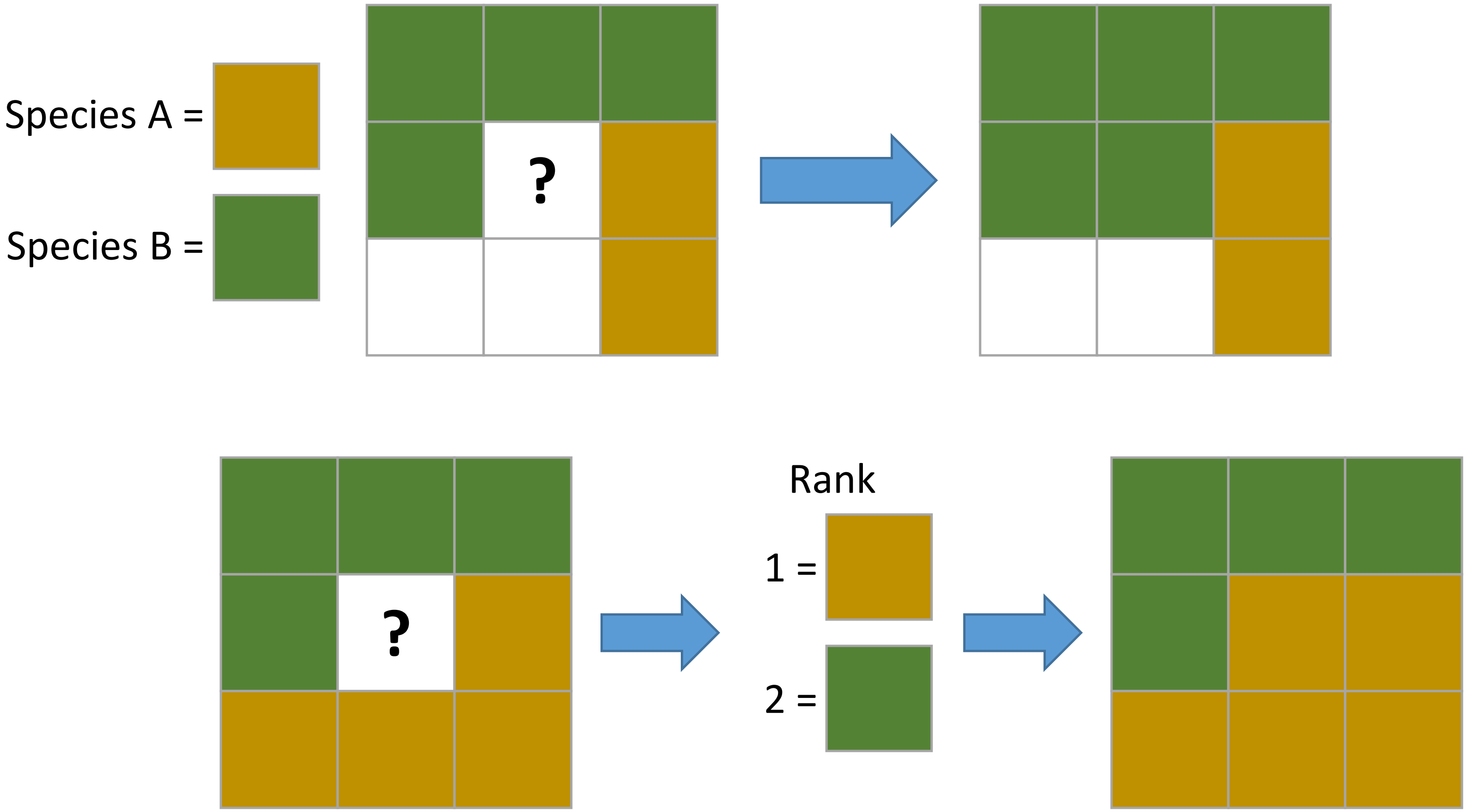
Species Mapping Project

Run MESMA on each height class, subsetting endmember list (www.vipertools.org)

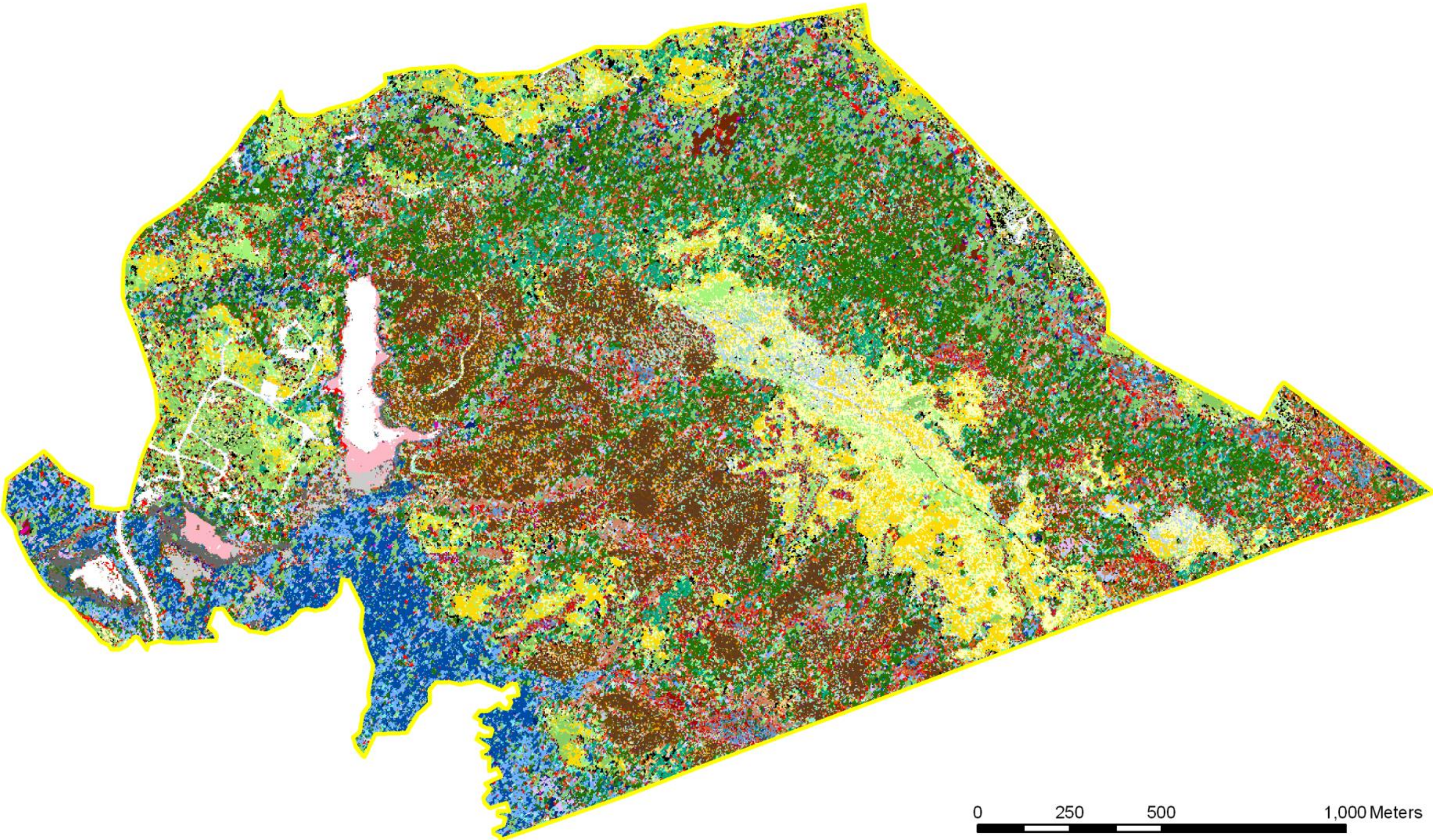


Species Mapping Project

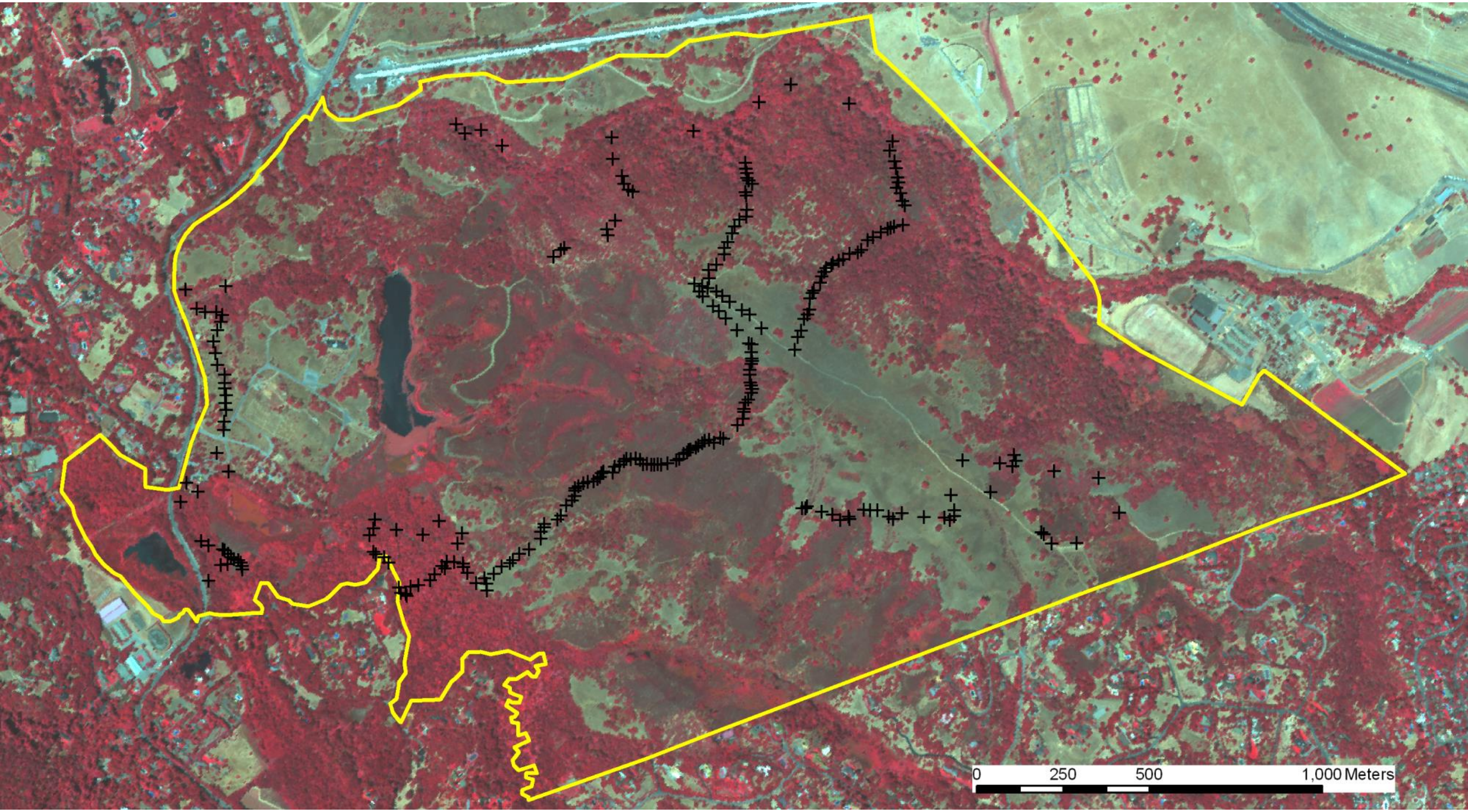
Ranked space-filling algorithm



Species Mapping Project
Species Map!



Species Mapping Project
Accuracy assessment



		Field Validation Data	
		Present	Absent
MESMA Data	Present	***a***	***b***
	Absent	***c***	***d***

Overall accuracy = $\frac{a+d}{n}$

Sensitivity = (User's accuracy) $\frac{a}{a+c}$

Specificity = (Producer's accuracy) $\frac{d}{b+d}$

True Skill Statistic (TSS) = $sensitivity + specificity - 1$

Latest Numbers

Overall Accuracy	Sensitivity	Specificity	TSS

Species Mapping Project

Accuracy assessment

		Field Validation Data	
		Present	Absent
MESMA Data	Present	***a***	***b***
	Absent	***c***	***d***

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Latest Numbers

Overall Accuracy	Sensitivity	Specificity	TSS
91.3%	33.9%	95.0%	0.29

Mapping Traits(!) (if there's time)

PNAS PNAS

Environmental and community controls on plant canopy chemistry in a Mediterranean-type ecosystem

Kyla M. Dahlin[a,b,1,2], Gregory P. Asner[b], and Christopher B. Field[b]

[a]Department of Biology, Stanford University, Stanford, CA 94305; and [b]Department of Global Ecology, Carnegie Institution for Science, Stanford, CA 94305

Edited by Robert E. Dickinson, University of Texas at Austin, Austin, TX, and approved March 12, 2013 (received for review September 6, 2012)

Understanding how and why plant communities vary across space has long been a goal of ecology, yet parsing the relative importance of different influences has remained a challenge. Species-specific models are not generalizable, whereas broad plant functional type models lack important detail. Here we consider plant trait patterns at the local scale and ask whether plant chemical traits are more closely linked to environmental gradients or to changes in species composition. We used the visible-to-shortwave infrared (VSWIR) spectrometer of the Carnegie Airborne Observatory to d… maps of four plant chemical traits—leaf nitrogen per ma… carbon per mass, leaf water concentration, and canopy wat… tent—across a diverse Mediterranean-type ecosystem (Jaspe…

critical to models operating across large regions and at coarse resolutions. Recent studies argue, however, that disturbances like fire (12), logging (13), and herbivory (14) play important roles even at global scales. The prevalence of these diffuse disturbances, combined with the well-recognized role of plant composition in ecosystem processes (15), suggests the need for assessing the sources of trait variation across large scales while still resolving the contributions of individual organisms to that variation.

Advances in airborne remote sensing can address some of these

pnas.org/content/110/17/6895.short

Ecological Applications, 24(7), 2014, pp. 1651–1669

Spectroscopic determination of leaf morphological and biochemical traits for northern temperate and boreal tree species

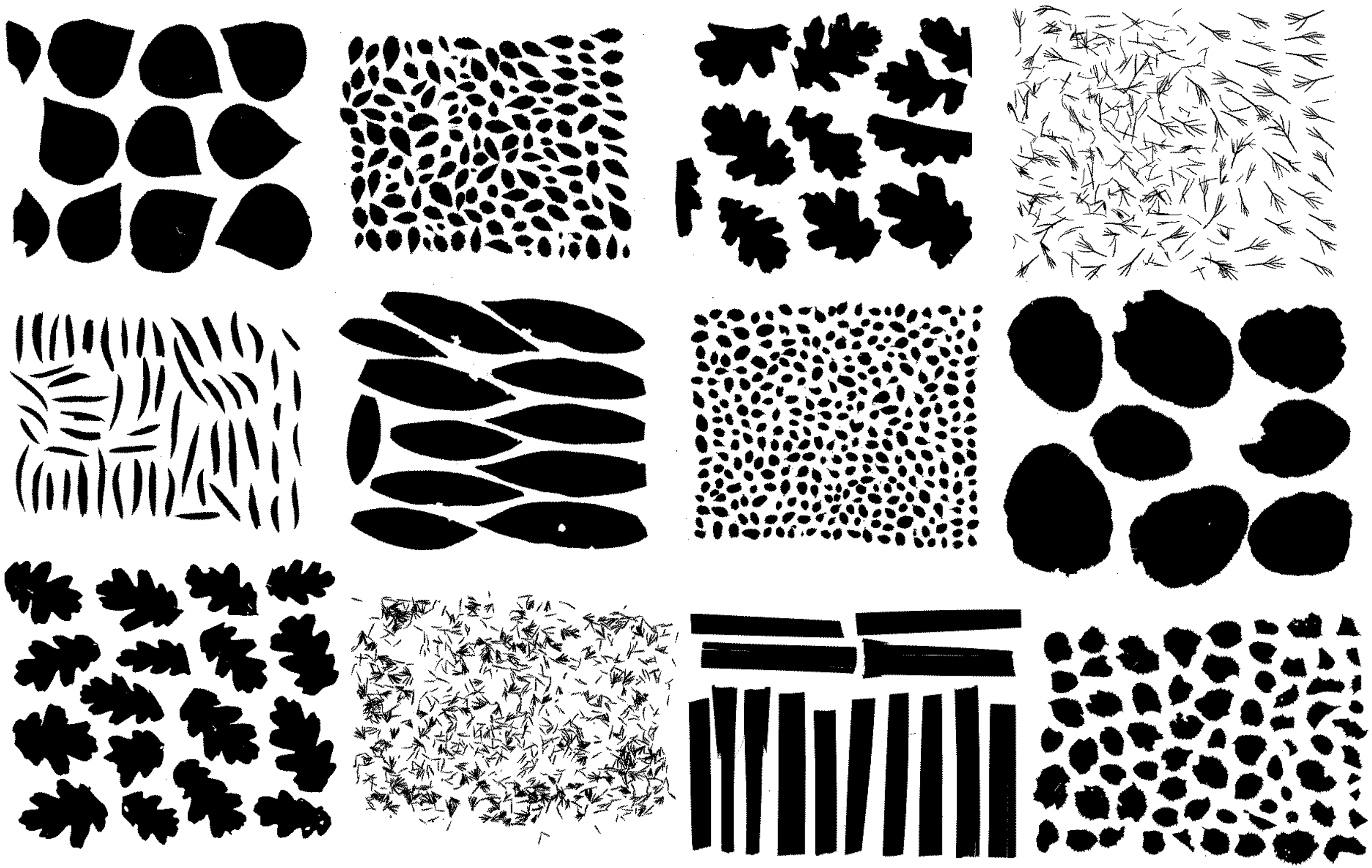
Shawn P. Serbin,[1,3] Aditya Singh,[1] Brenden E. McNeil,[2] Clayton C. Kingdon,[1] and Philip A. Townsend[1]

[1]*Department of Forest and Wildlife Ecology, University of Wisconsin, Madison, Wisconsin 53706 USA*
[2]*Department of Geology and Geography, West Virginia University, Morgantown, West Virginia 26506 USA*

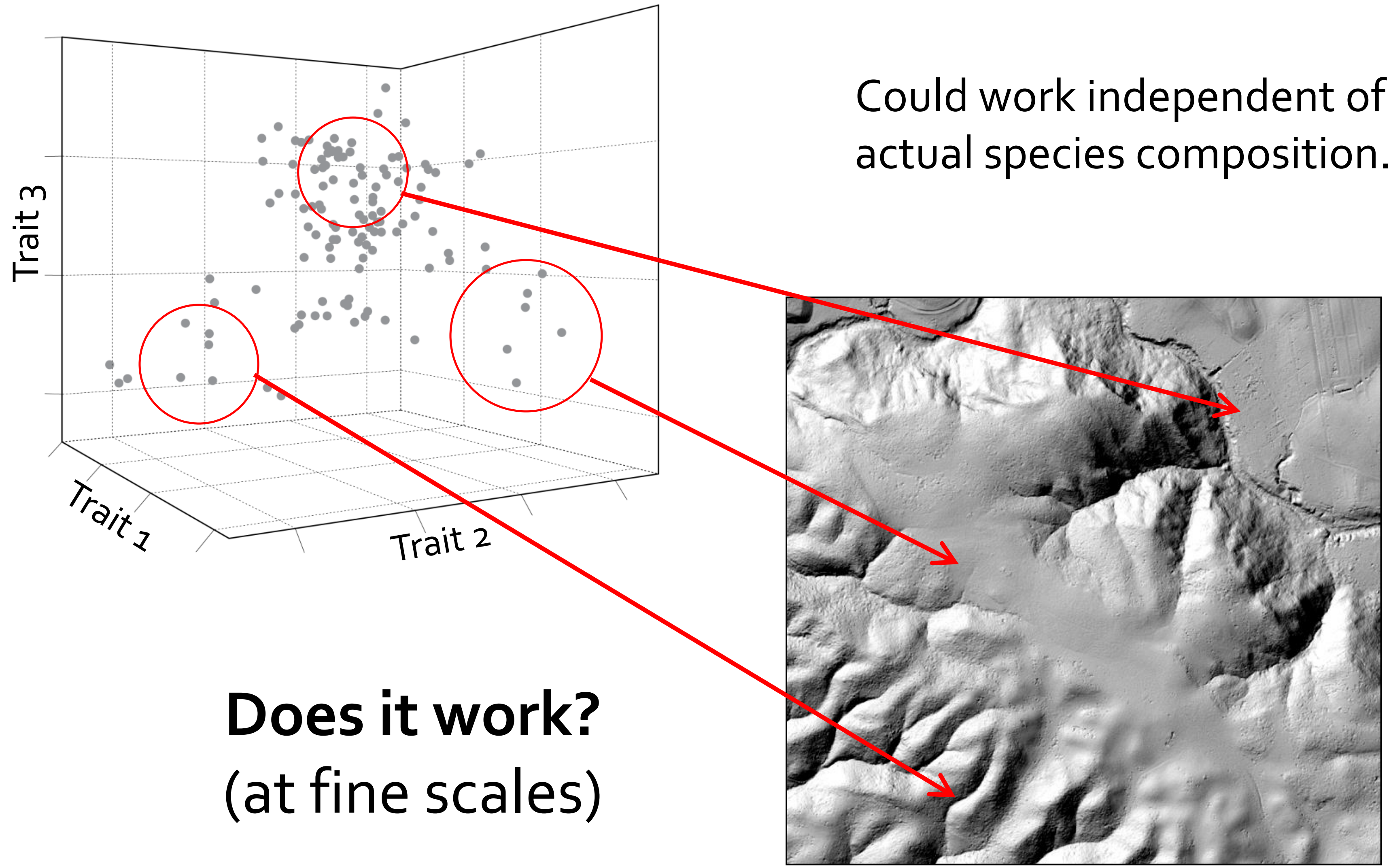
Abstract. The morphological and biochemical properties of plant canopies are strong predictors of photosynthetic capacity and nutrient cycling. Remote sensing research at the leaf and canopy scales has demonstrated the ability to characterize the biochemical status of vegetation canopies using reflectance spectroscopy, including at the leaf level and canopy level from air- and spaceborne imaging spectrometers. We developed a set of accurate and precise spectroscopic calibrations for the determination of leaf chemistry (contents of nitrogen, carbon, and fiber constituents), morphology (leaf mass per area, M_{area}), and isotopic composition ($\delta^{15}N$) of temperate and boreal tree species using spectra of dried and ground leaf material. The data set consisted of leaves from both broadleaf and needle-leaf conifer species and displayed a wide range in values, determined with standard analytical approaches: 0.7–4.4% for nitrogen (N_{mass}), 42–54% for carbon (C_{mass}), 17–58% for fiber (acid-digestible fiber, ADF), 7–44% for lignin (acid-digestible lignin, ADL), 3–31% for cellulose, 17–265 g/m^2 for

esajournals.org/doi/abs/10.1890/13-2110.1

What are plant traits?



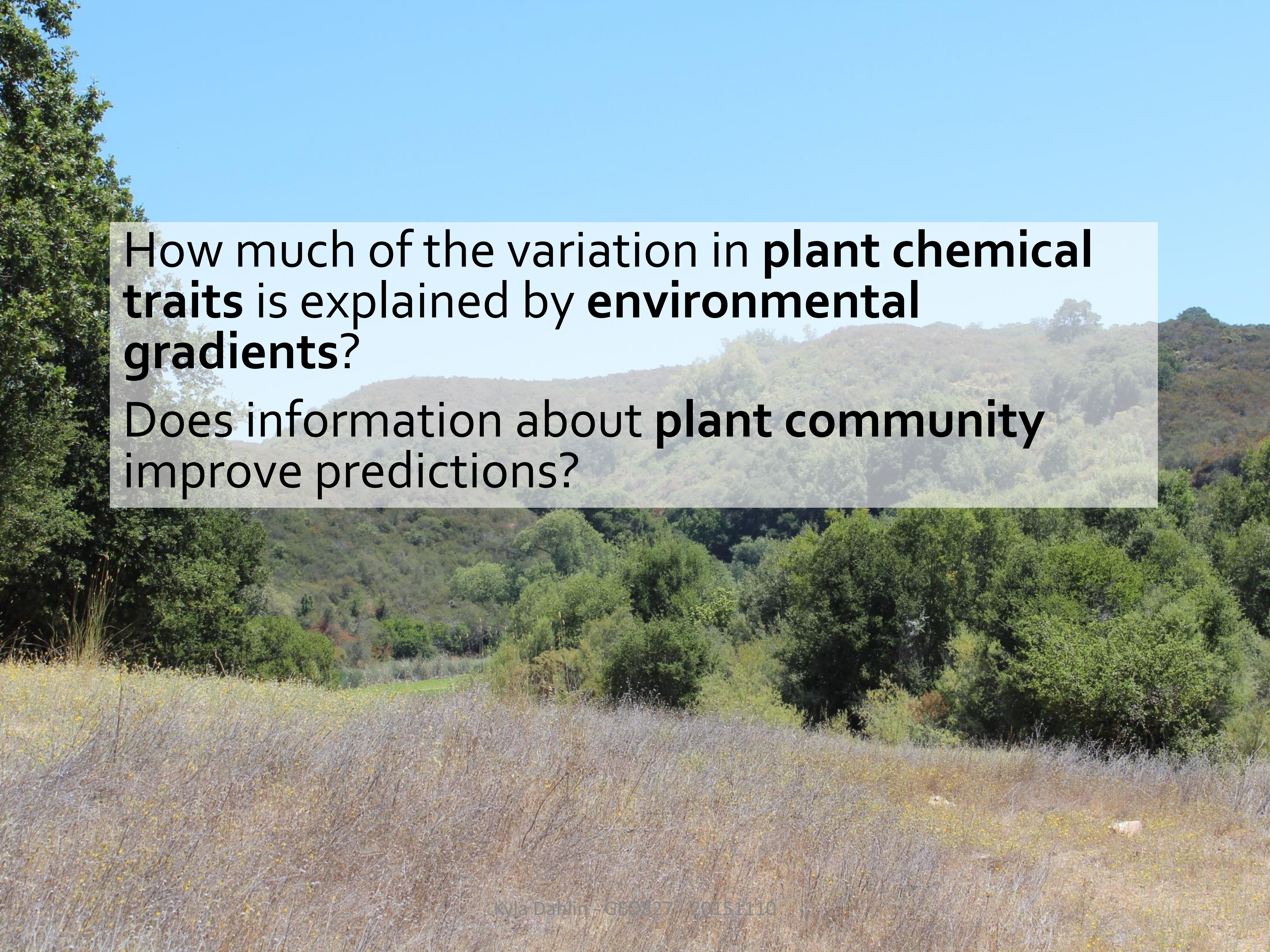
Motivation



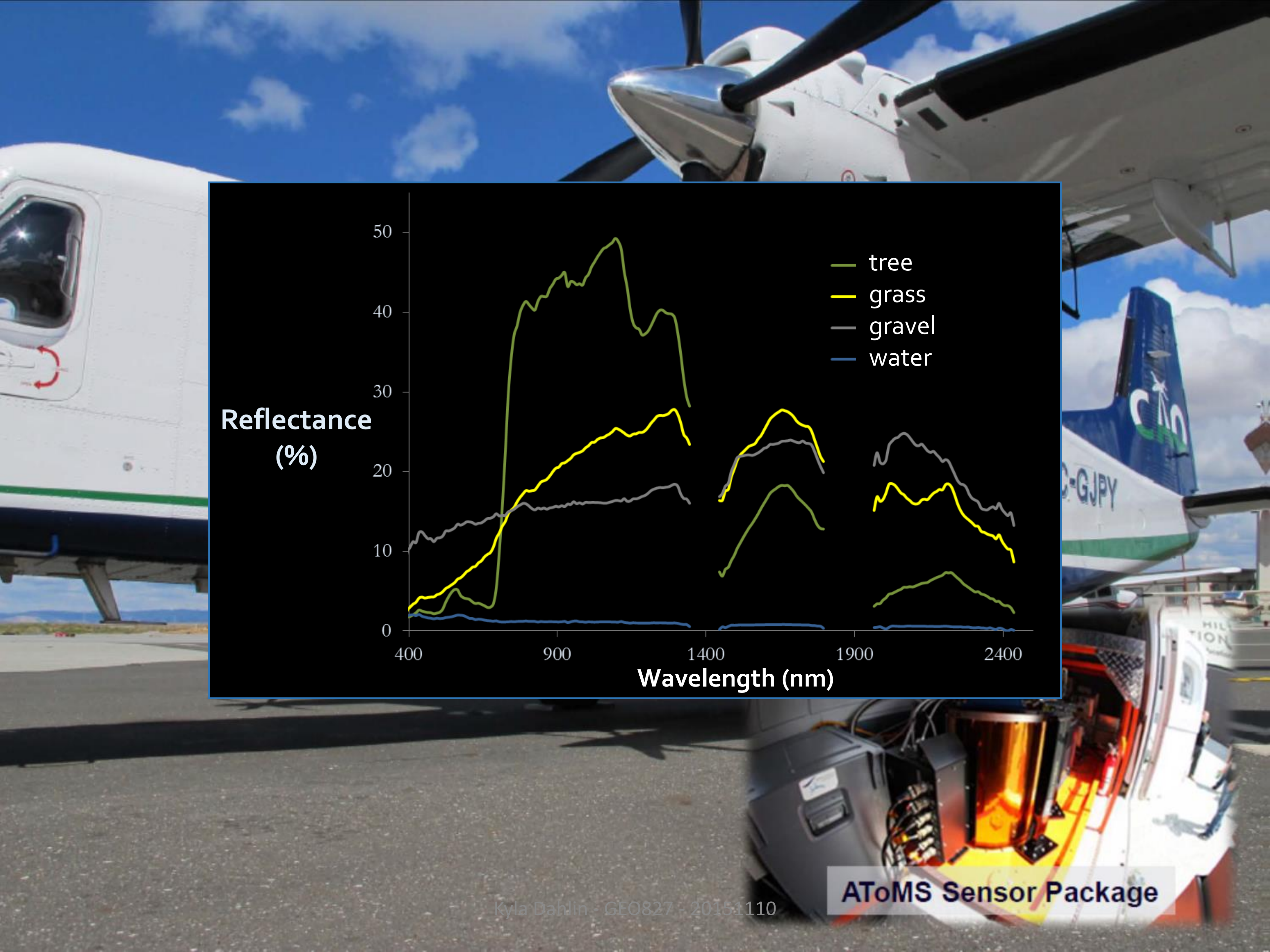
Could work independent of actual species composition.

Does it work?
(at fine scales)

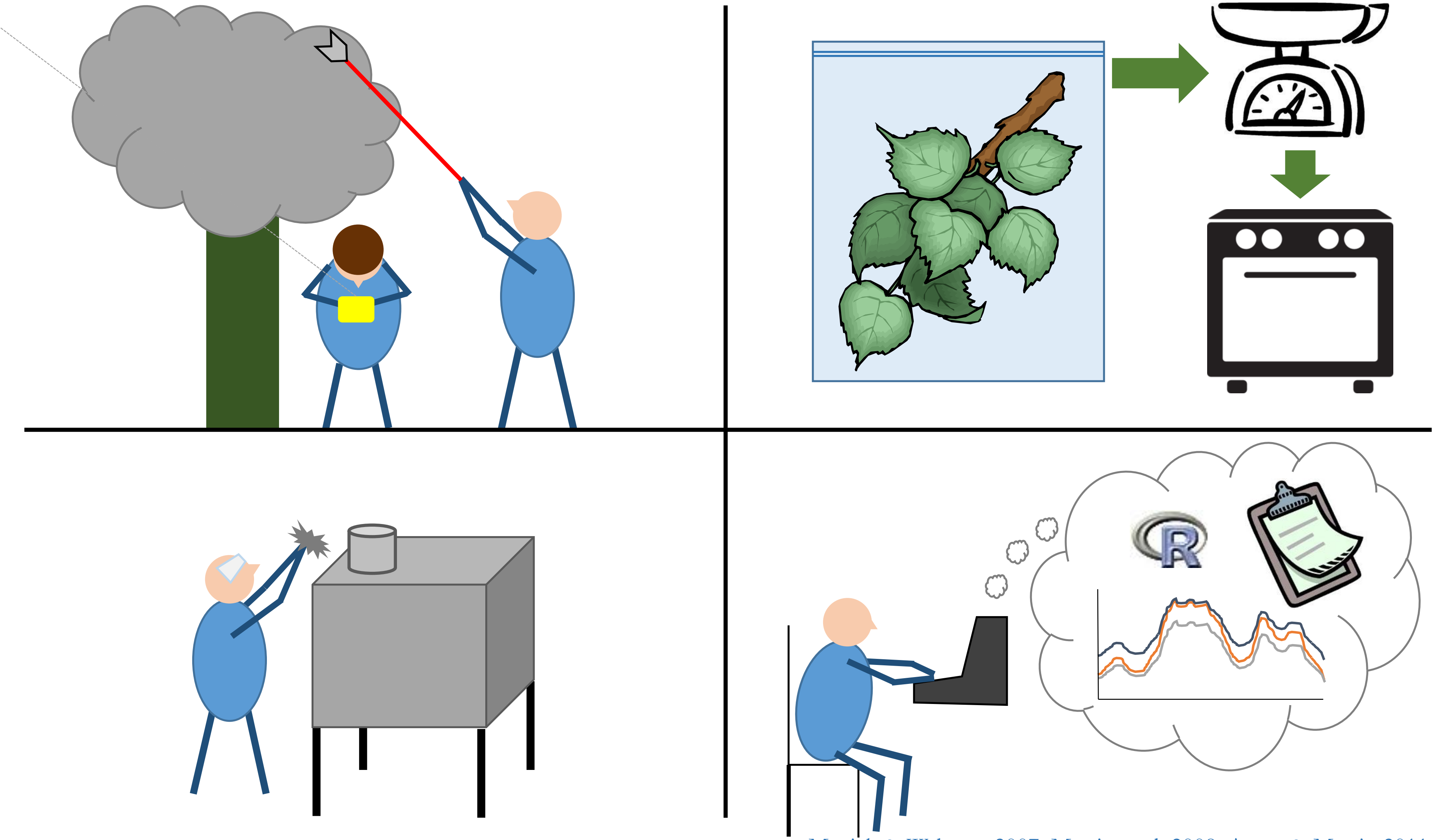
McGill et al 2006


How much of the variation in **plant chemical traits** is explained by **environmental gradients**?
Does information about **plant community** improve predictions?

cao.carnegiescience.edu


tree
grass
gravel
water
Reflectance (%)
50
40
30
20
10
0
400
900
1400
1900
2400
Wavelength (nm)
AToMS Sensor Package

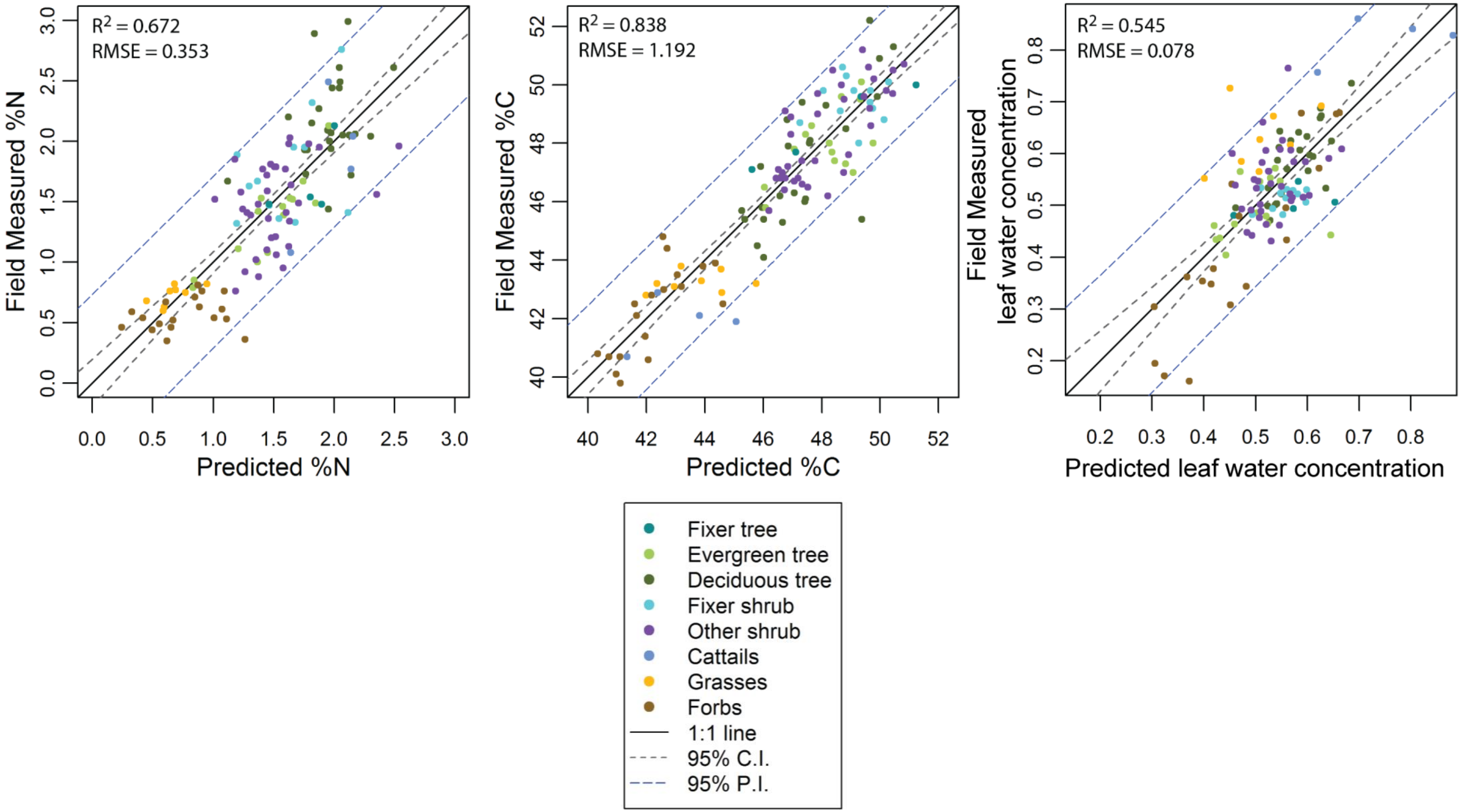
Methods



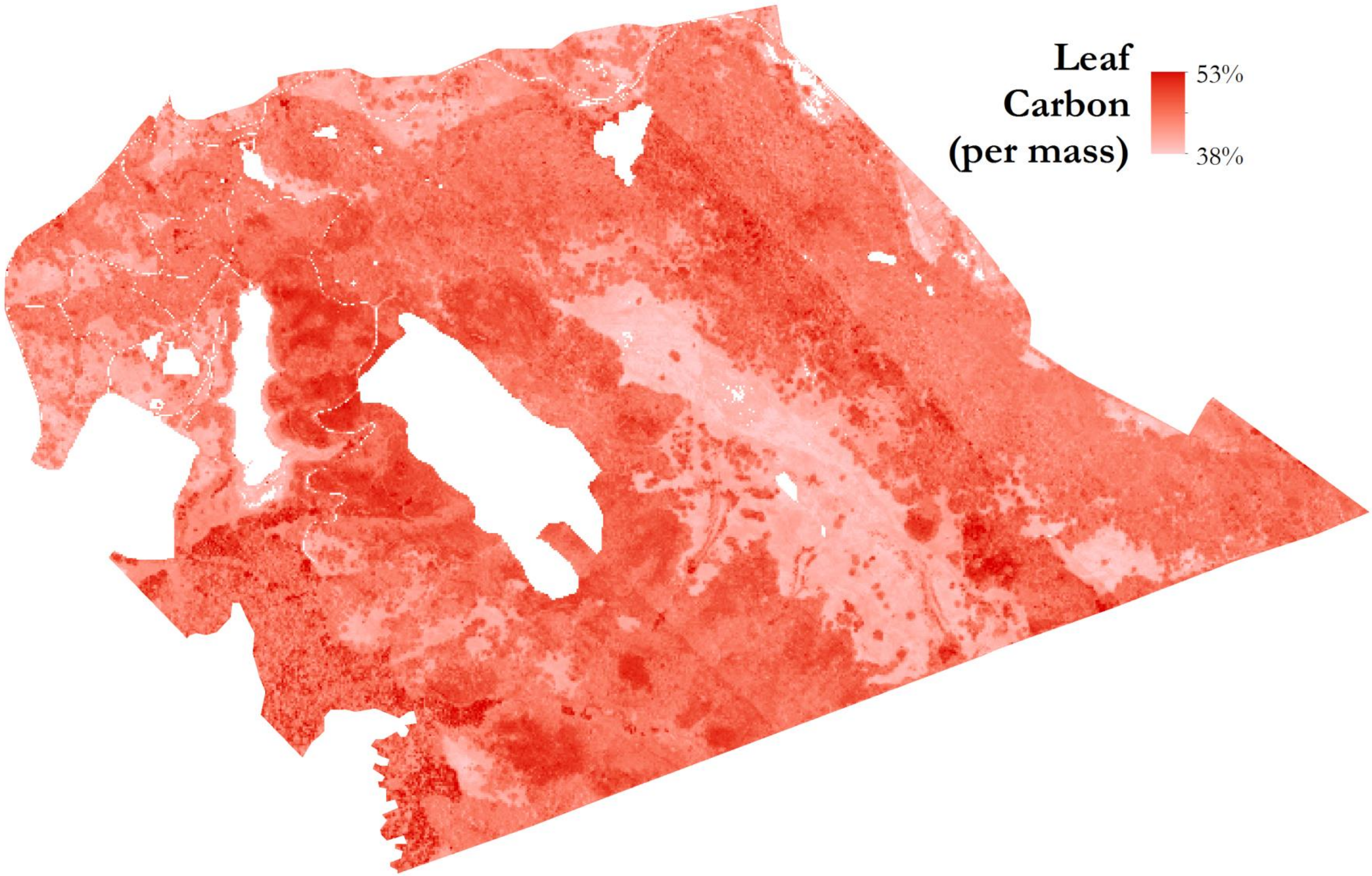
Mevick & Wehrens 2007, Martin et al. 2008, Asner & Martin 2011

PLSR Results

(Partial Least Squares Regression)



Mapped Canopy Traits



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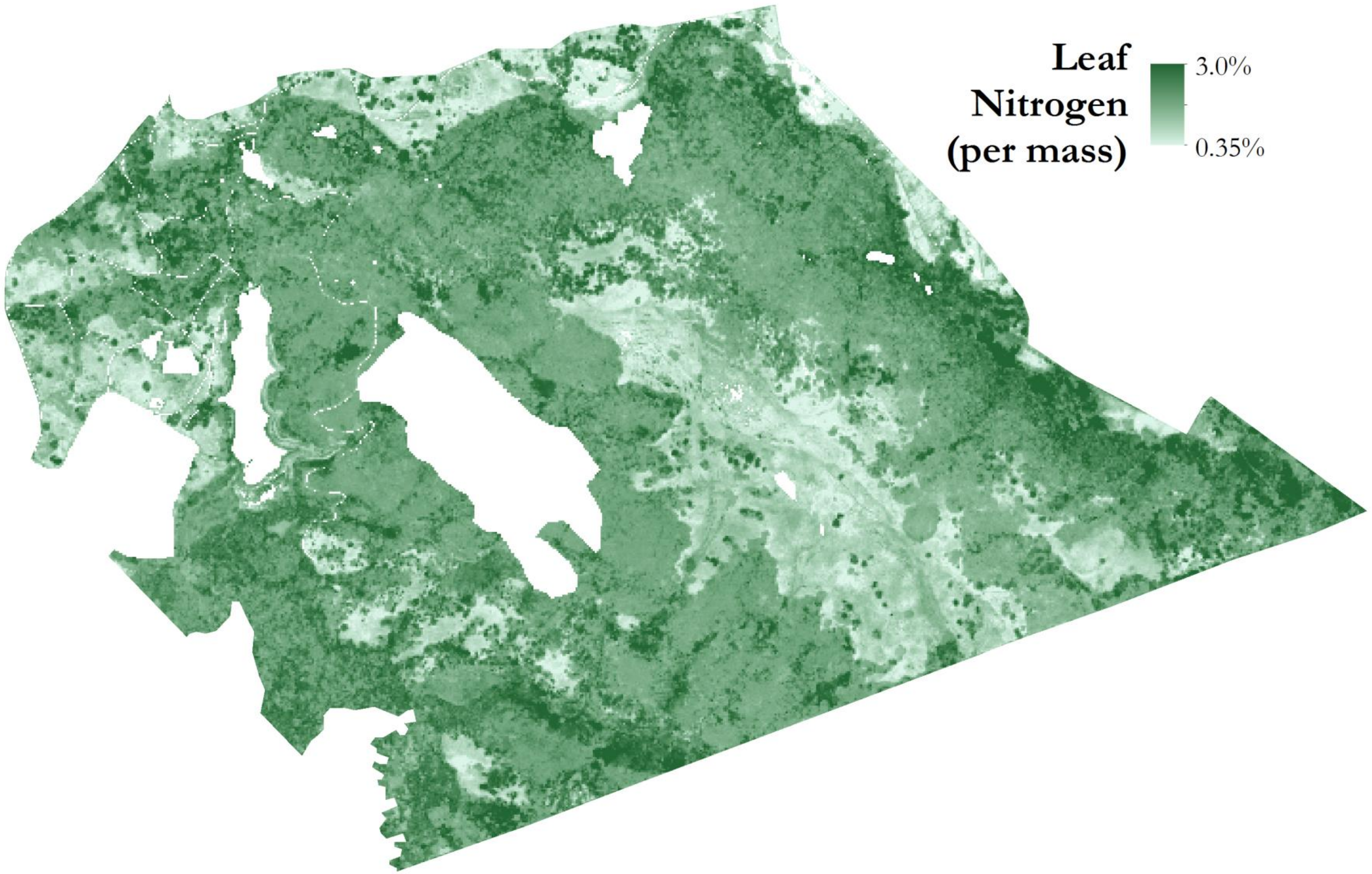
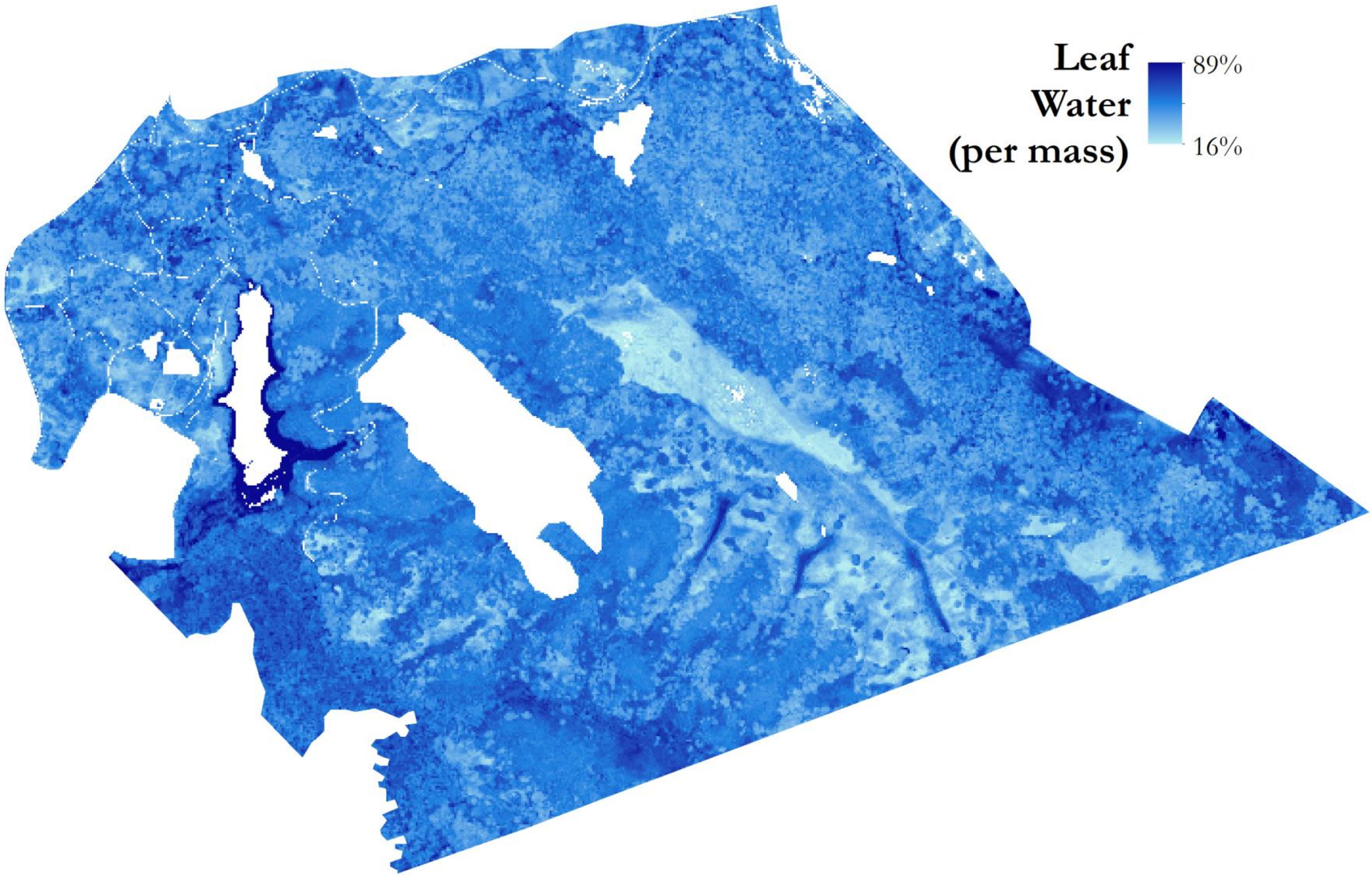
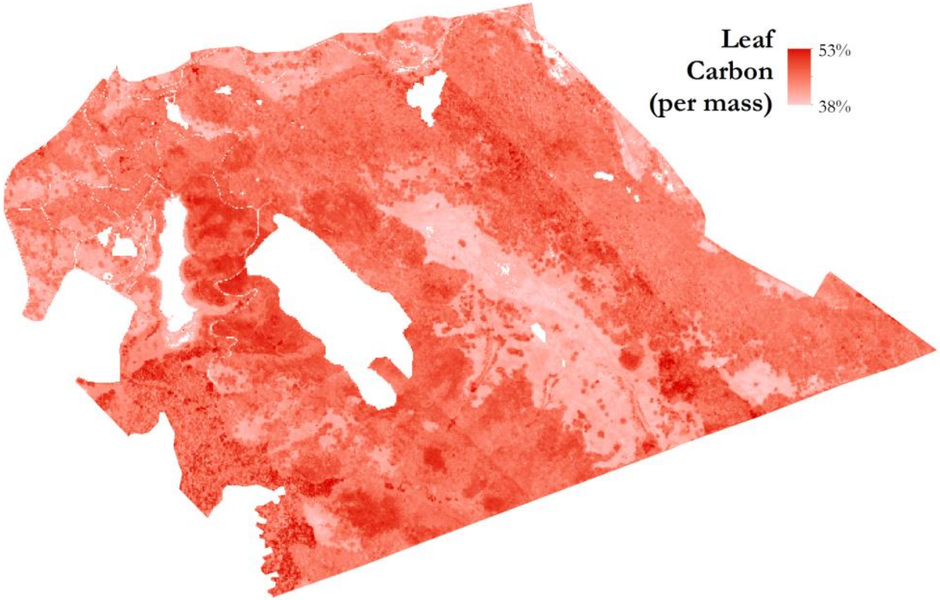
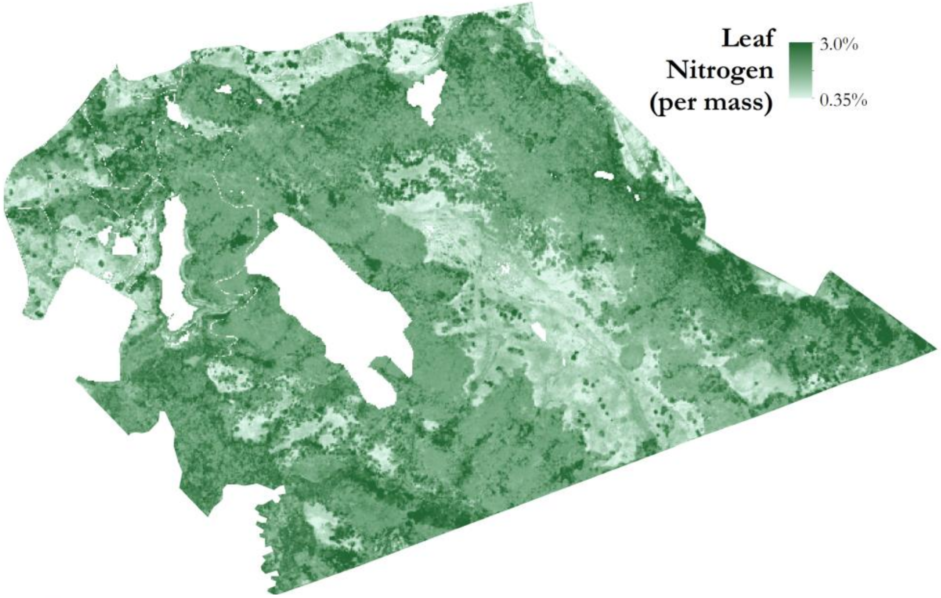


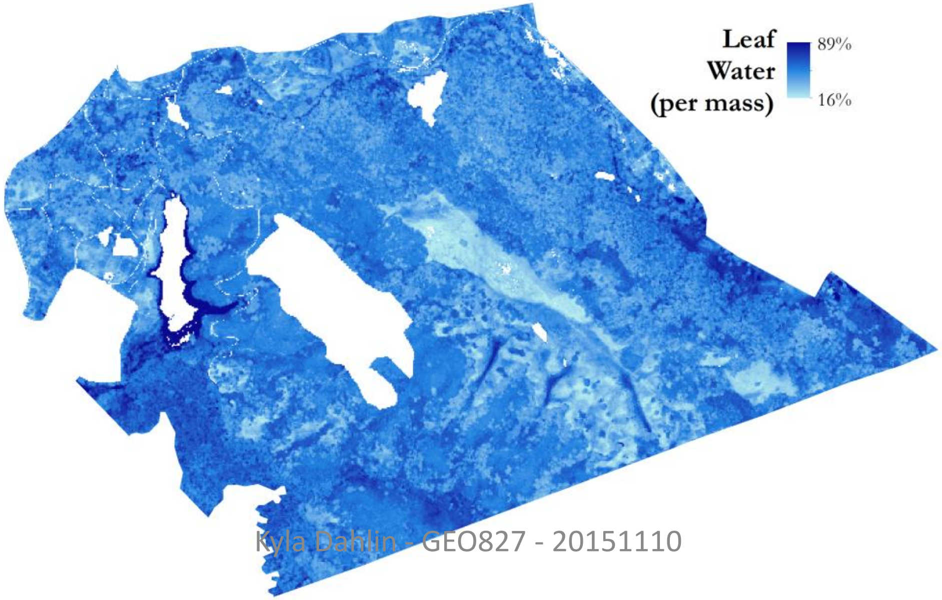
Mapped Canopy Traits



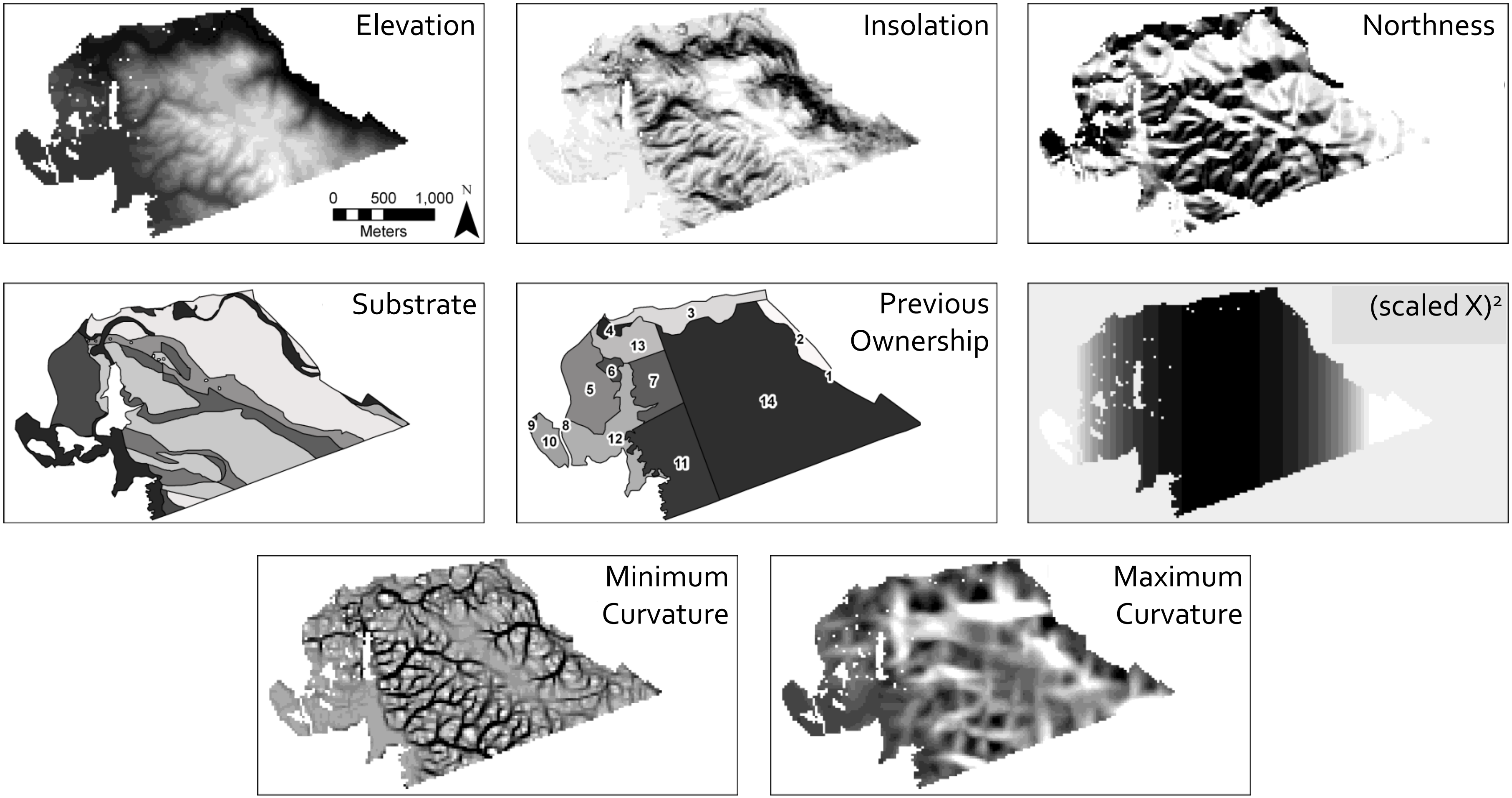
Mapped Canopy Traits



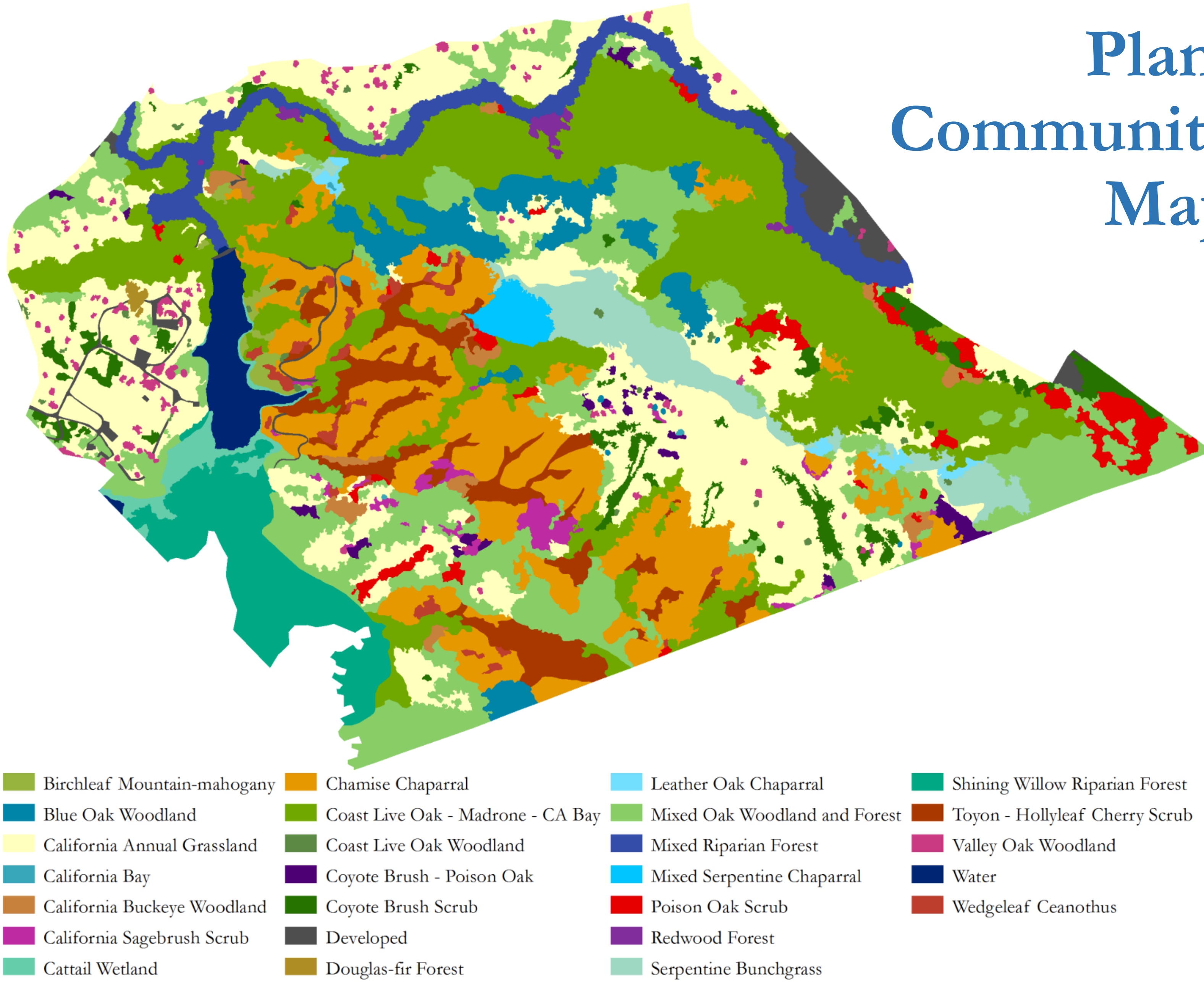




Environmental Gradients, etc.



Plant Community Map



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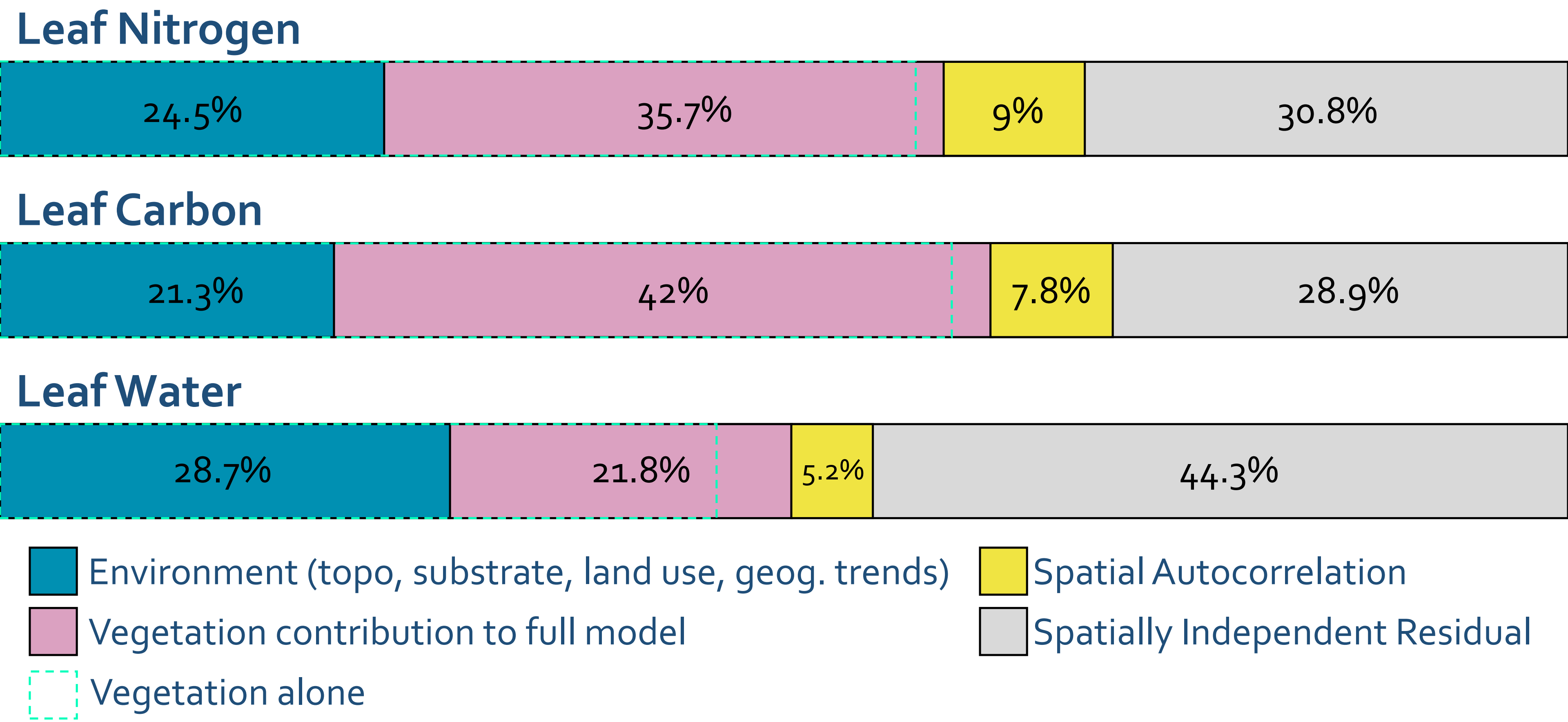
Simultaneous Autoregression

Haining 2003, Bivand et al. 2012

Results: Variation Explained



Conclusions

How much of the variation in **plant chemical traits** is explained by **environmental gradients**?

~25%

Does information about **plant community** improve predictions?

Yes, by > double.

Why?

Unmapped environmental gradients, land use history, dispersal limitation, competition, etc.

Thanks!

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