Functional ecology in the SBG Era: An assessment of the state of plant trait retrieval from imaging spectroscopy



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Plant functional traits

Measurable characteristics of plants that are closely related to function and fitness.



Leaf traits affect leaf optical properties, allowing us to estimate leaf traits from remote measurements of reflectance ("imaging spectroscopy").



(1) What are the "best" algorithms, at both leaf and

"Boring! Make new algorithms!" - NASA review panel Fine, we'll make new algorithms! - Shiklomanov et al.

(2) Why do these algorithms succeed (or fail), and under what conditions?

(3) How should we measure spectra to get the best

trait estimates?

canopy scales?

"Too late -- nobody cares!" - NASA review panel Fine, we'll look at flowers instead! - Shiklomanov et al.

New algorithms: Bayesian alternative to PLSR



Alternative approach: **Bayesian Regression**

Traditional approach:

Partial Least Squares Regression (PLSR)

 $w_1^P x_{400} + \dots w_{2400}^P x_{2400}$

Comparable performance to PLSR for estimating leaf %N (and other traits) from field spectroscopy.



 $trait = \beta_1 PLSR_1 + \dots \beta_p PLSR_p$

 $w_1^1 x_{400} + \dots w_{2400}^1 x_{2400}$

Additional advantages

2.5

5.0

- Propagate uncertainty
- Leverage prior information

0.0

beta

Conceptually simple

-2.5

Extensible (e.g., multivariate)

Why do these algorithms succeed (or fail), and under what conditions?



All these traits have been successfully mapped using imaging spectroscopy. Why does this work? What are we really seeing when we see "invisible" traits, in terms of correlations with other traits, structure, etc.

Dr. Dhruva Kathuria

(3) Flowers!









SBG High-Frequency Time series (SHIFT) — Weekly AVIRIS-NG flights during spring/summer 2021, with coordinated field sampling.

Dr. Yoseline Angel

Mapping flowers and their phenology

RENDVI =

Mapping flowers using Gaussian mixture model (GMM)

Probability of Occurrence

Spectral clusters $p(\theta)$ maps + uncertainties

Certainty



Species reported by **Wildflower Search*** shows the phenological dynamics of C. Gigantea and A. Californica, observed during their flowering phase



Dr. Yoseline Angel

Enabling large-scale SHIFT data analysis with cloud computing

SHIFT SMCE User Guide

latest

Search docs

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Juypter Notebook Basics

Storage Options

Ξ	Working	With	Datasets	

Loading SHIFT Data with Intake
Reading in Data
Working with L1 and L2a Data
Orthorectifying a Dataset
Xarray Basics
Visualizing Data
Raster Operations
Clustering Example
Downloading Datasets

Reading in Data

Data can be read in using two function calls: read and read_chunked. The read method will pull all the data in the dataset into memory. It is highly recommended to use the read_chunked method unless you are sure your data can fit into memory.

xarray.Dataset				
- Dimensions:	(time: 13, y: 12023, wa	velength: 425, x	: 13739)	
▼ Coordinates:				
time	(time)	datetime64[us]	2022-02-24 2022-05-29	
wavelength	(wavelength)	float32	377.2 382.2 2.496e+03 2.501e+03	
х	(X)	float64	7.177e+05 7.177e+05 7.864e+05	
У	(y)	float64	3.866e+06 3.866e+06 3.806e+06	
▼ Data variables:				
	(time v wavelength v)	float32	dask arrav <chunksize=(1 1="" 1373<="" 425="" td=""><td>B</td></chunksize=(1>	B
reflectance	(unie, y, wavelength, x)	noacoz	australity - anality - (1, 1, 423, 1313	

Evan Lang

https://shift-smce-user-guide.readthedocs.io

SHIFT project on NASA Science Managed Cloud Environment (SMCE) provides cloud-based interactive analysis capabilities (JupyterLab), scalable compute (SLURM) next to the SHIFT airborne data, and tools and documentation to make all of this easier!

Spectra Selection

3.819+6

3.819e+6

3.819e+

7.303e+5 7.304e+5 7.305e+5 7.306e+5 7.307e+5 7.308e+5 7.309e+57.310e+

```
# Create the RGB image plot
rgb_image = ds_rgb.hvplot.rgb(
   x='x', y='y', bands='wavelength', aspect = 'equal', frame_width=400).opts(
   tools=["hover", 'lasso_select'])
# Create streams
posxy = hv.streams.PointerXY(source=rgb image, x=730302.5, y=-3819657.5)
sel = hv.streams.Lasso(source=rgb_image, geometry=np.array([[730302.5, 3819657.5]]))
# Function to build a new spectral plot based on mouse hover positional
# Information retrieved from the RGB image using our full reflectance dataset
def point_spectra(x,y):
   return aoi.sel(x=x,y=y,method='nearest').hvplot.line(
       y='reflectance',x='wavelength', color='#1b9e77', frame_width=400)
def selected_info(geometry):
   x = find_nearest(aoi.x, geometry[:, 0])
   y = find_nearest(aoi.y, geometry[:, 1])
   points = set(list(zip(x, y)))
   list_of_lines = [aoi.sel(x=x, y=y, method='nearest').hvplot.line(
       y='reflectance',x='wavelength', frame_width=400) for x, y in points]
   return hv.Overlay(list_of_lines)
# Define the Dynamic Maps
point_dmap = hv.DynamicMap(point_spectra, streams=[posxy])
lasso_dmap = hv.DynamicMap(selected_info, streams=[sel])
# Plot the RGB image and Dynamic Maps side by side
(rgb_image + point_dmap*lasso_dmap)
                                                                      time = 2022-03-08, x = 7.303e+05, y = 3.819e+06
                                                  0.8 -
 3.820#+
                                                  0.6
 3.820e+6
                                                 0.4
 3.819e+6
```

1500 wavelength

Extensions to cloud platforms to support new use cases



Evan Lang

New algorithms for trait retrieval



trait ~ $N(\theta, \sigma)$

 $\sigma \sim halfCauchy(0,\alpha)$



Bayesian

Mapping flowers and their phenology



