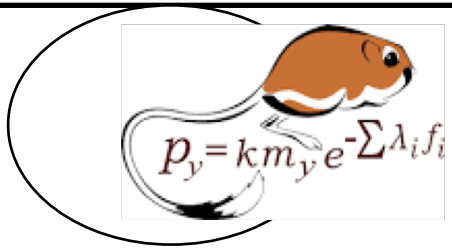
UF Biodiversity Institute
University of Florida

SCALING UP REMOTE SENSING FUNDAMENTAL UNIT: FROM PIXEL TO CROWNS

Inferring forest structure and traits syndromes for each individual tree within NEON forest sites

Sergio Marconi, Sarah J. Graves, Jeremy Lichstein Aditya Singh, Stephanie Bohlman, Ethan P. White



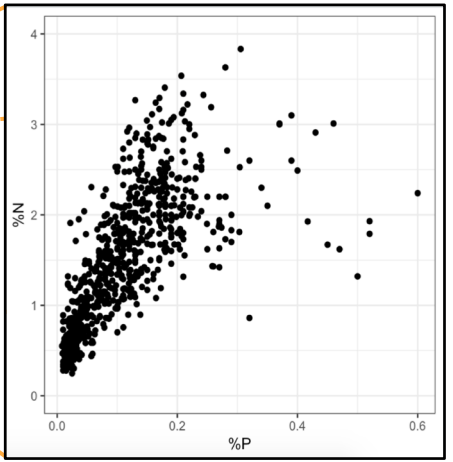
GORDON AND BETTY MOORE FOUNDATION

NIST National Institute of Standards and Technology

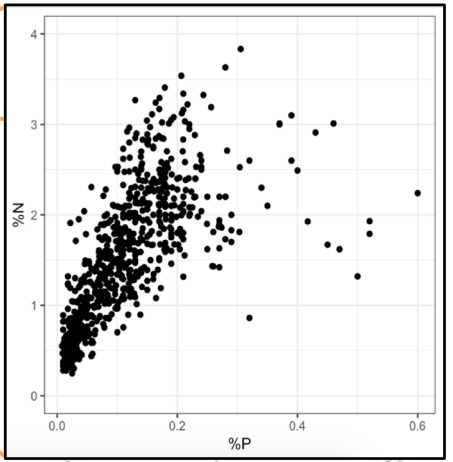
HOW DOES SPATIAL STRUCTURE INFLUENCE ECOSYSTEM FUNCTION AND HOW DO WE INTEGRATE WITHIN AND BETWEEN SPATIAL SCALES TO ASSESS FUNCTION?

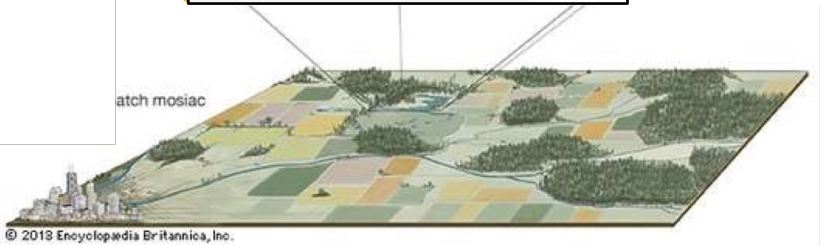
Sutherland, William J., et al. "Identification of 100 fundamental ecological questions." *Journal of ecology* 101.1 (2013): 58-67.

PROCESSES AND PATTERNS ARE SCALE DEPENDENT

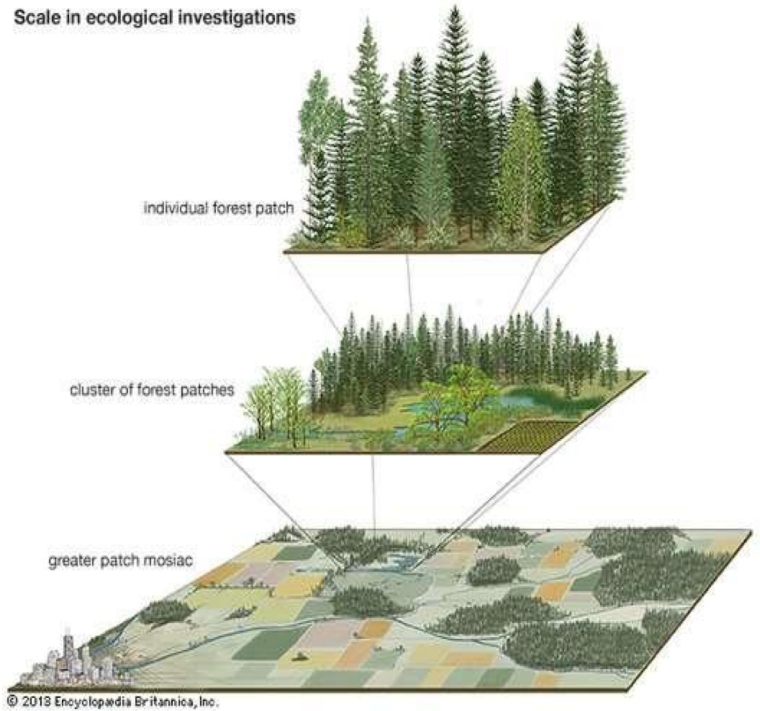


PROCESSES AND PATTERNS ARE SCALE DEPENDENT



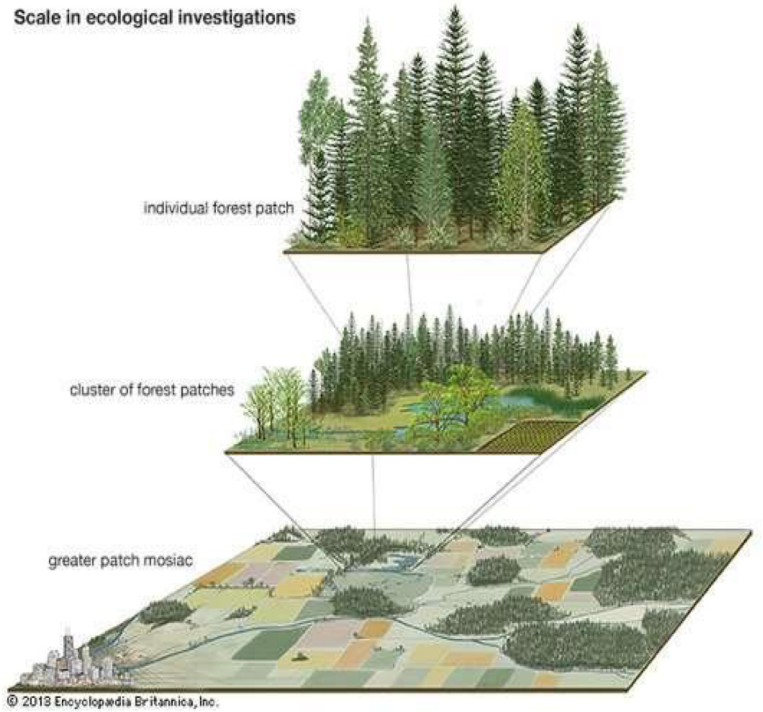


PROCESSES AND PATTERNS ARE SCALE DEPENDENT

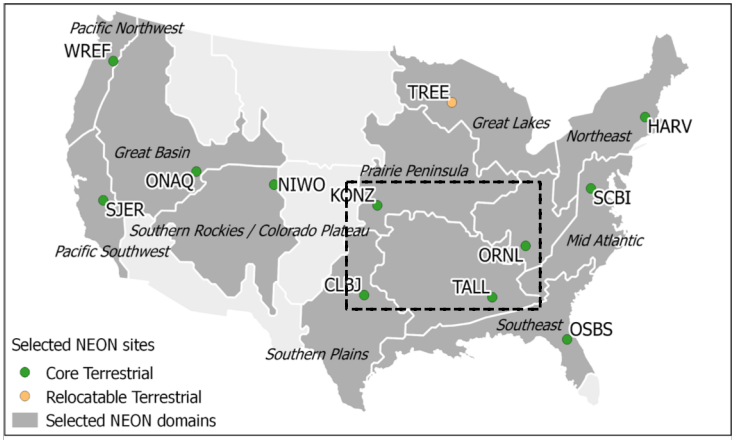


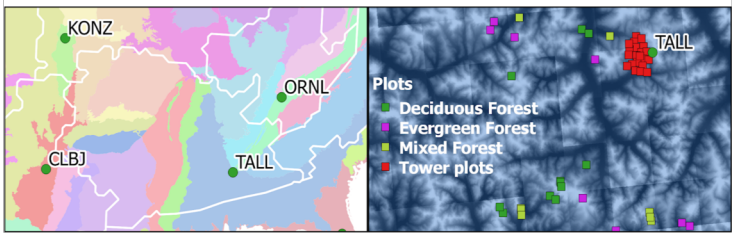
Niinemets, Ülo. "Is there a species spectrum within the world-wide leaf economics spectrum? Major variations in leaf functional traits in the Mediterranean sclerophyll Quercus ilex." New Phytologist 205.1 (2015): 79-96.

HOW CAN WE INVESTIGATE CROSS SCALE PATTERSN AND PROCESSES?

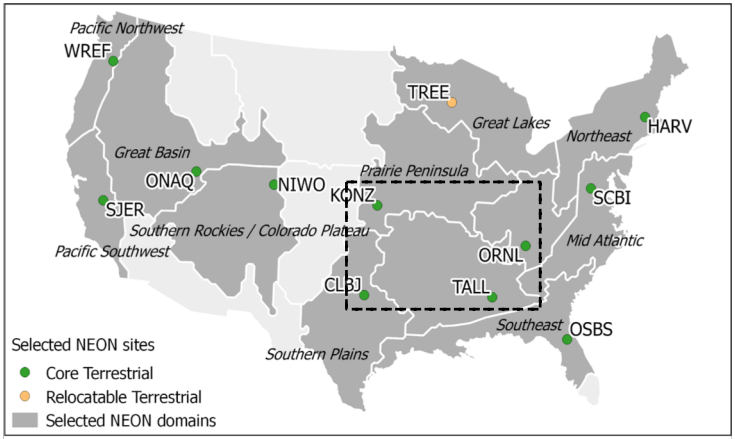


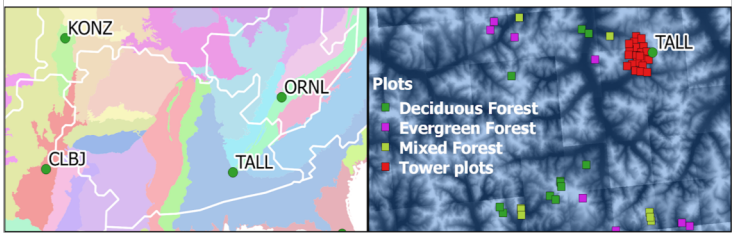
THE ROLE OF THE NATIONAL ECOLOGICAL OBSERVATORY NETWORK

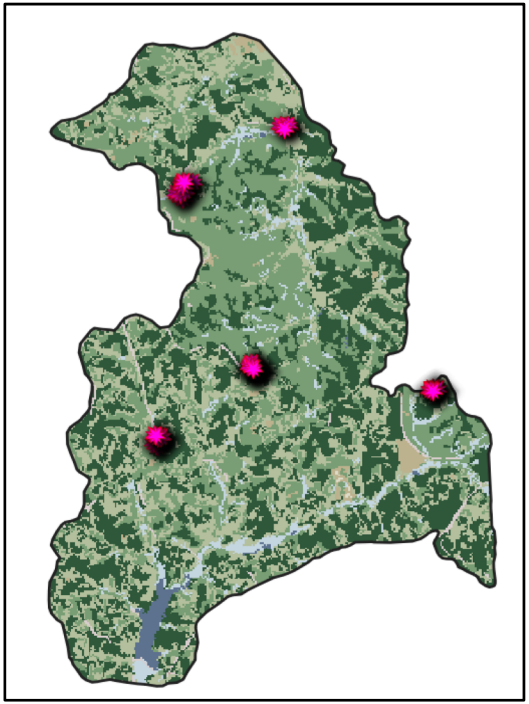




IS NEON TERRESTRIAL DATA ENOUGH?

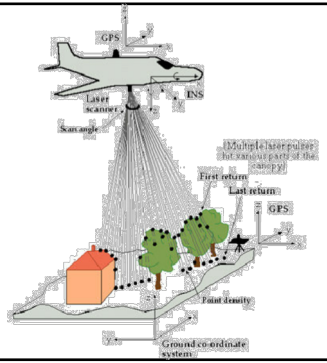


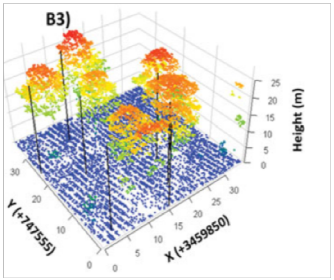


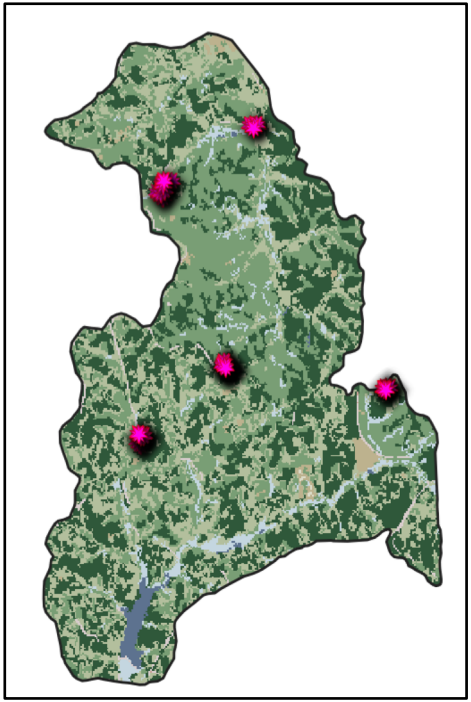


NEON AIRBORNE DATA: AN OPPORTUNITY TO SCALE AT FINE SCALE

LiDAR

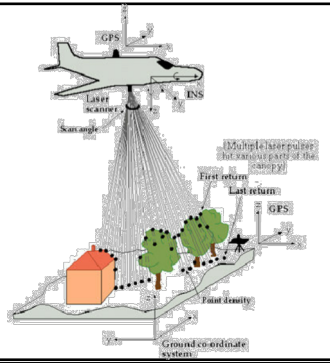


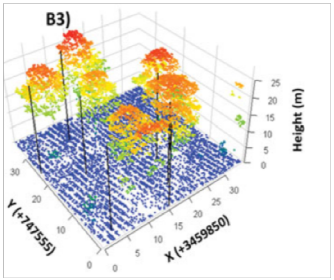




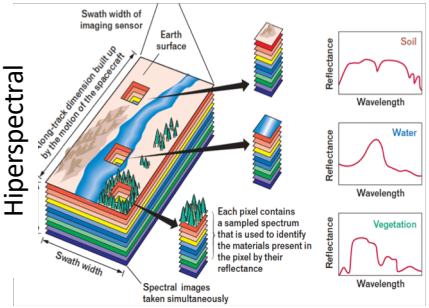
NEON AIRBORNE DATA: AN OPPORTUNITY TO SCALE AT FINE SCALE

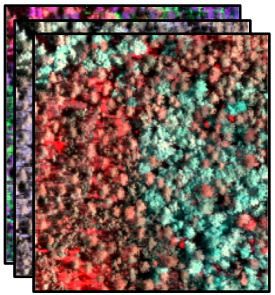
LiDAR

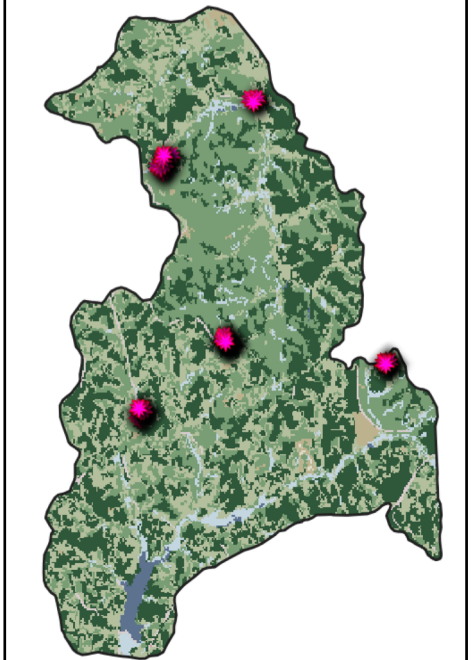




Hiperspectral





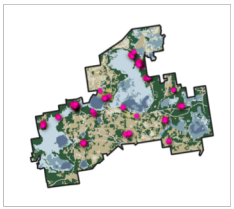


INTEGRATION OF TERRESTRIAL AND REMOTE SENSING DATA

Field?

- Precise, direct measurement

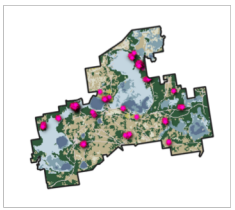
- Expensive
- Potentially biased



INTEGRATION OF TERRESTRIAL AND REMOTE SENSING DATA: WHAT

Field?

- Precise, direct measurement
- Expensive
- Potentially biased



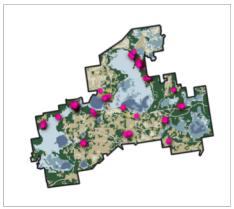
Pixel?

- Provides continuous estimates on wide areas
- Automatable, unbiased
- Indirect measure
- No biological meaning

INTEGRATION OF TERRESTRIAL AND REMOTE SENSING DATA: WHAT

Field?

- Precise, direct measurement
- Expensive
- Potentially biased

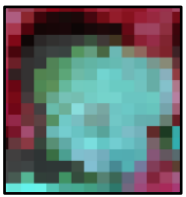


Pixel?

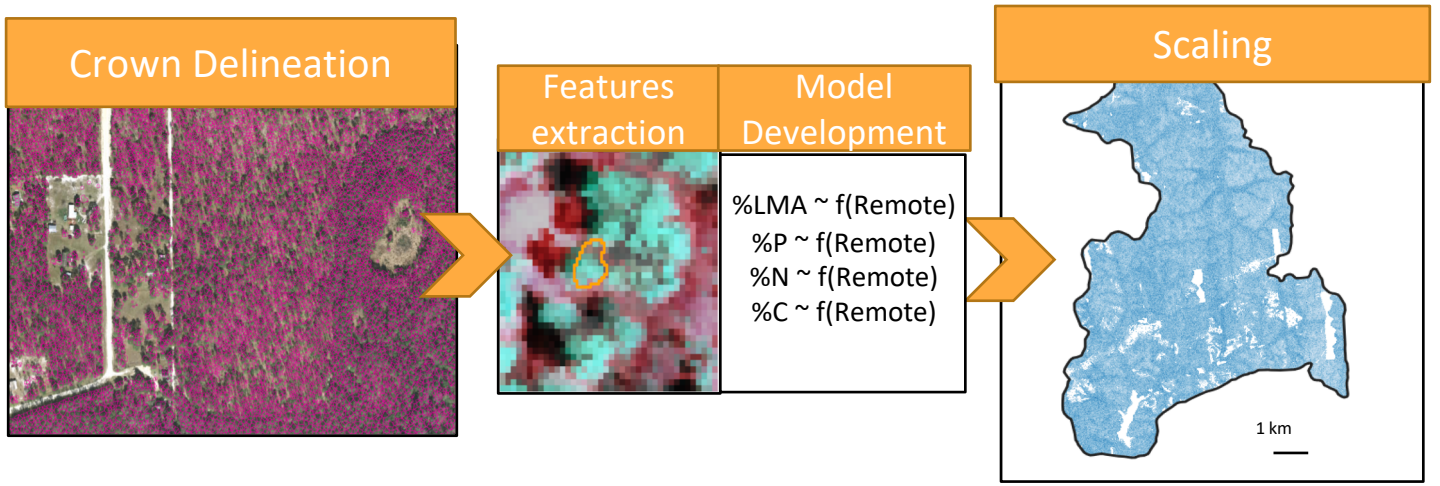
- Provides continuous estimates on wide areas
- Automatable, unbiased
- Indirect measure
- No biological meaning

Crown object?

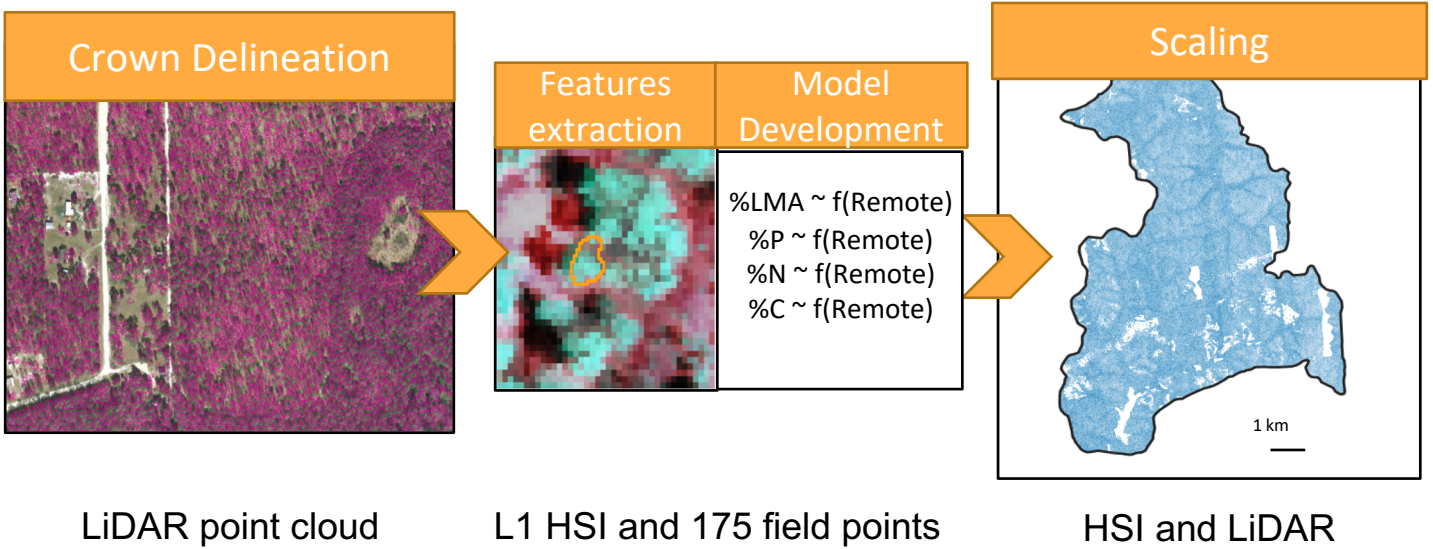
???



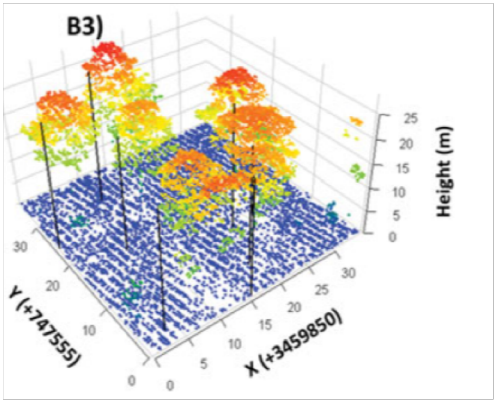
MODULAR PIPELINE

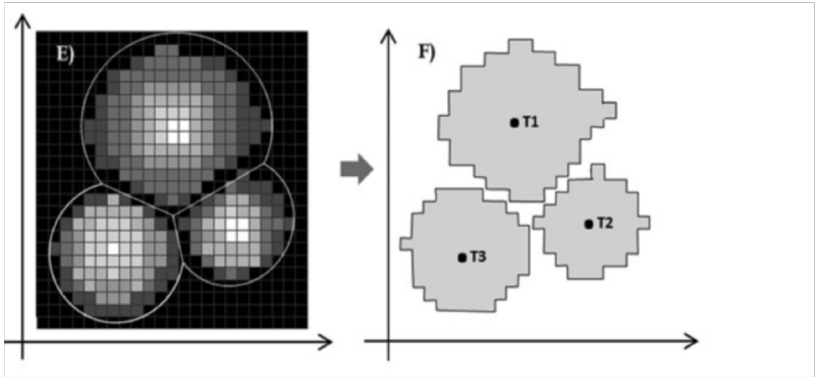


MODULAR PIPELINE



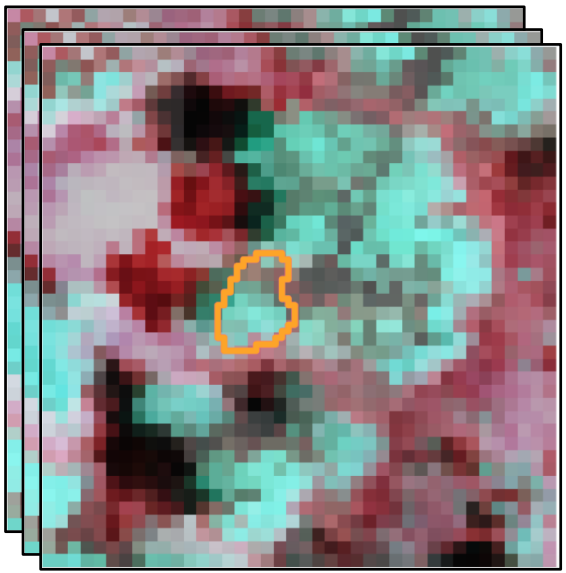
CROWN DELINEATION





Silva, Carlos A., et al. "Imputation of individual Longleaf Pine (Pinus palustris Mill.) Tree attributes from field and LiDAR data." *Canadian journal of remote sensing* 42.5 (2016): 554-573.

FEATURES EXTRACTION AND MODEL DEVELOPMENT



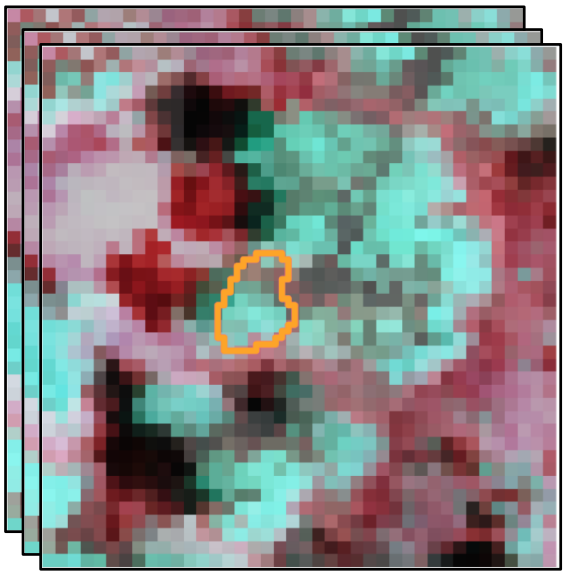
MULTIPLE INSTANCE PROBLEM: A.K.A.
SEVERAL Xi PER SINGLE VALUE Yi

$$\begin{Bmatrix} X_{p1,b1} & X_{p1,b2} & \dots & X_{p1,b369} \\ X_{p2,b1} & X_{p2,b2} & \dots & X_{p2,b369} \\ \dots & \dots & \dots & \dots \\ X_{pN,b1} & X_{pN,b2} & \dots & X_{pN,b369} \end{Bmatrix} \sim Yi$$

Xi

CROWN PIXELS x FEATURES

FEATURES EXTRACTION AND MODEL DEVELOPMENT



MULTIPLE INSTANCE PROBLEM: A.K.A. SEVERAL Xi PER SINGLE VALUE Yi

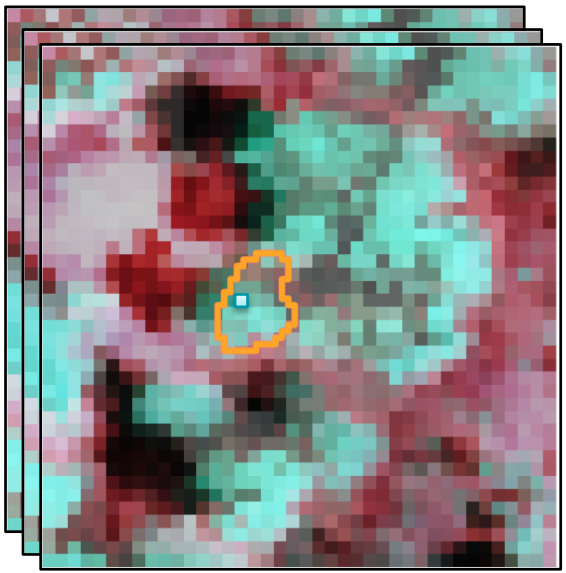
Each matrix contain GOOD, BAD, and (good/bad) FALSE POSITIVE pixels

$$\begin{Bmatrix} X_{p1,b1} & X_{p1,b2} & \dots & X_{p1,b369} \\ X_{p2,b1} & X_{p2,b2} & \dots & X_{p2,b369} \\ \dots & \dots & \dots & \dots \\ X_{pN,b1} & X_{pN,b2} & \dots & X_{pN,b369} \end{Bmatrix} \sim Yi$$

Xi

CROWN PIXELS x FEATURES

HOW CAN WE USE INFORMATION FROM ALL?



MULTIPLE INSTANCE PROBLEM: A.K.A.
SEVERAL Xi PER SINGLE VALUE Yi

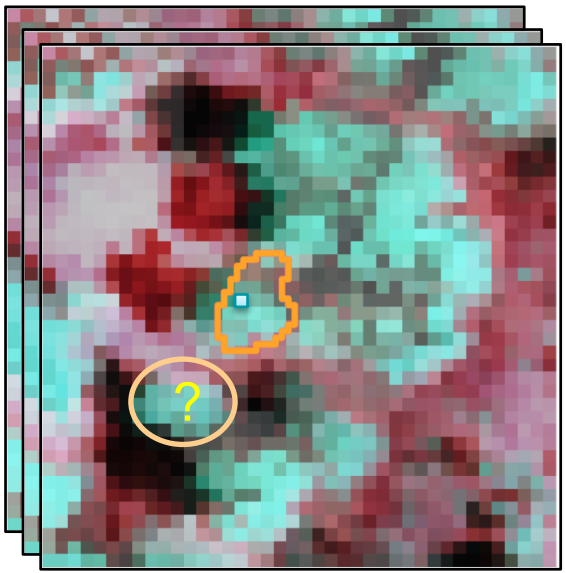
Each matrix contain GOOD, BAD, and (good/bad) FALSE POSITIVE pixels

$$\begin{Bmatrix} X_{p1,b1} & X_{p1,b2} & \dots & X_{p1,b369} \\ X_{p2,b1} & X_{p2,b2} & \dots & X_{p2,b369} \\ \dots & \dots & \dots & \dots \\ X_{pN,b1} & X_{pN,b2} & \dots & X_{pN,b369} \end{Bmatrix} \sim Yi$$

Xi

CROWN PIXELS x FEATURES

HOW CAN WE USE INFORMATION FROM ALL?



MULTIPLE INSTANCE PROBLEM: A.K.A.
SEVERAL Xi PER SINGLE VALUE Yi

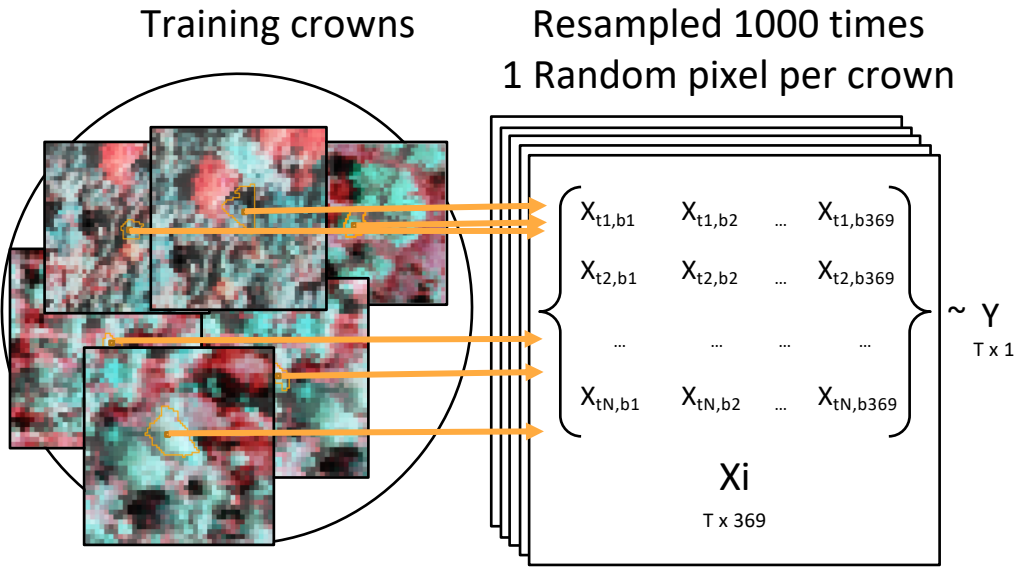
Each matrix contain GOOD, BAD, and (good/bad) FALSE POSITIVE pixels

$$\begin{Bmatrix} X_{p1,b1} & X_{p1,b2} & \dots & X_{p1,b369} \\ X_{p2,b1} & X_{p2,b2} & \dots & X_{p2,b369} \\ \dots & \dots & \dots & \dots \\ X_{pN,b1} & X_{pN,b2} & \dots & X_{pN,b369} \end{Bmatrix} \sim Yi$$

Xi

CROWN PIXELS x FEATURES

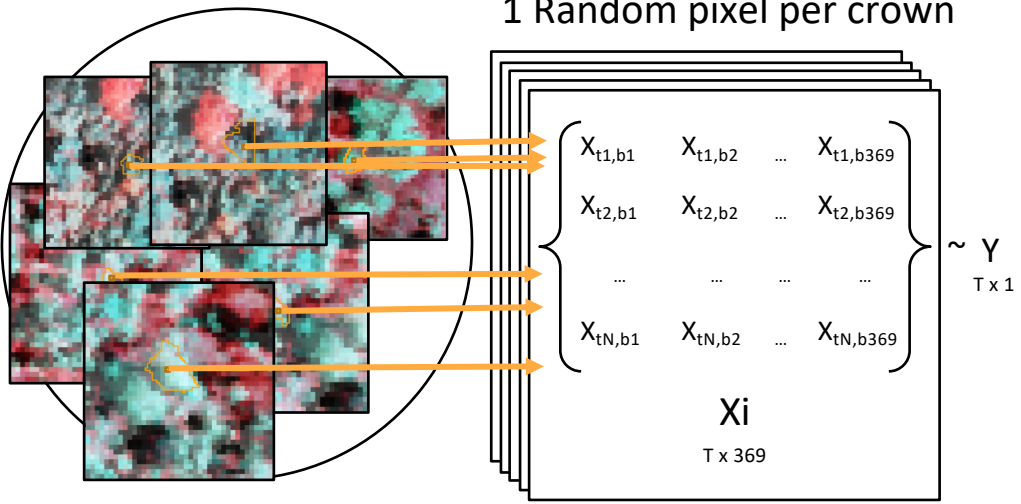
PARTIAL LEAST SQUARES GENERALIZED LINEAR ENSEMBLE



PARTIAL LEAST SQUARES GENERALIZED LINEAR ENSEMBLE

Training crowns

Resampled 1000 times
1 Random pixel per crown



Partial Least Square
Generalized Linear Regression

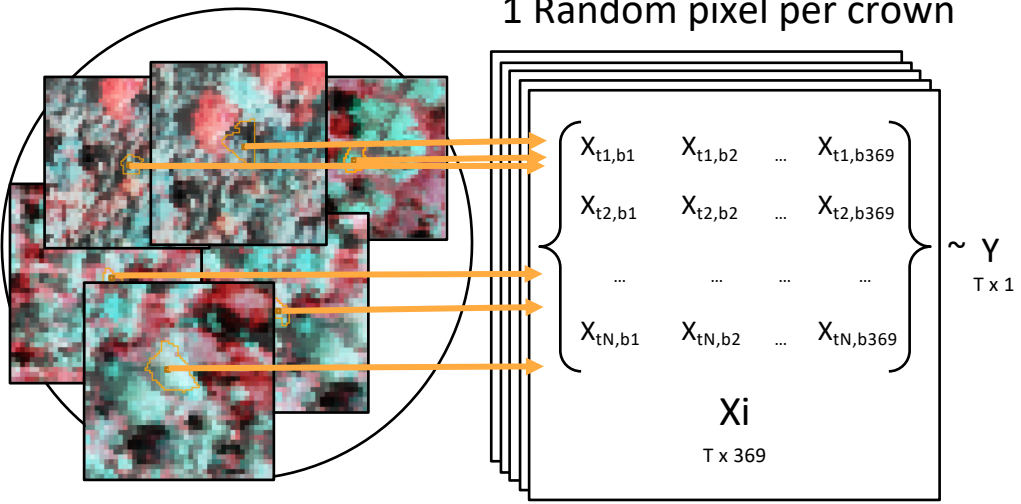
Principal components calculated using MLE

$$g(\theta) = \sum_{d=1}^{D} c_d \left(\sum_{j=1}^{p} w_{dj}^{*} x_j \right)$$

PARTIAL LEAST SQUARES GENERALIZED LINEAR ENSEMBLE

Training crowns

Resampled 1000 times
1 Random pixel per crown



Partial Least Square
Generalized Linear Regression

Principal components calculated using MLE

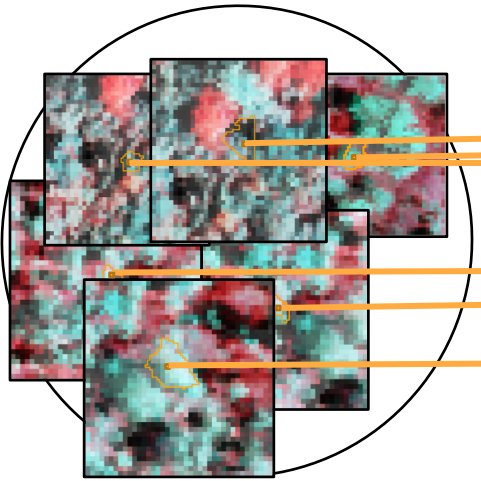
$$g(\theta) = \sum_{d=1}^{D} c_d \left(\sum_{j=1}^{p} w_{dj}^{*} \, x_j \right)$$

$$\hat{y} = \sum_{m=1}^{M=1000} g(\theta)_m \, \omega_m$$

$$\omega_m = softmax(\partial AIC)$$

PARTIAL LEAST SQUARES GENERALIZED LINEAR ENSEMBLE

Training crowns



Resampled 1000 times
1 Random pixel per crown

$X_{t1,b1}$	$X_{t1,b2}$	...	$X_{t1,b369}$
$X_{t2,b1}$	$X_{t2,b2}$	...	$X_{t2,b369}$
...	...	...	...
$X_{tN,b1}$	$X_{tN,b2}$	...	$X_{tN,b369}$

Xi

T x 369

~ Y

T x 1

Partial Least Square Generalized Linear Regression

Principal components calculated using MLE

$$g(\theta) = \sum_{d=1}^{D} c_d \left(\sum_{j=1}^{p} w_{dj}^{*} \, x_j \right)$$

$$\hat{y} = \sum_{m=1}^{M=1000} g(\theta)_m \, \omega_m$$

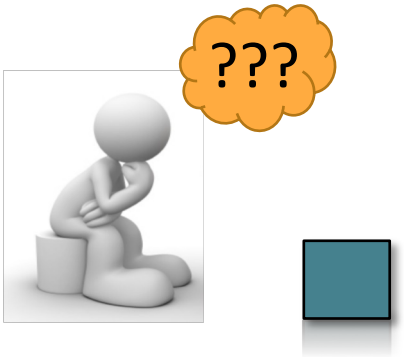
$$\omega_m = softmax(\partial AIC)$$

Ensemble

ADVANTAGES OF LABELING PIXELS WITH CROWN IDs

Pixel?

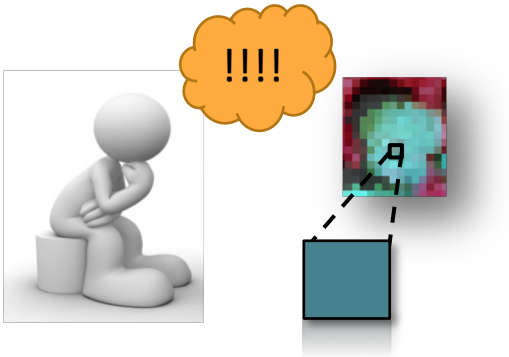
- No crown labelling
- No ensemble



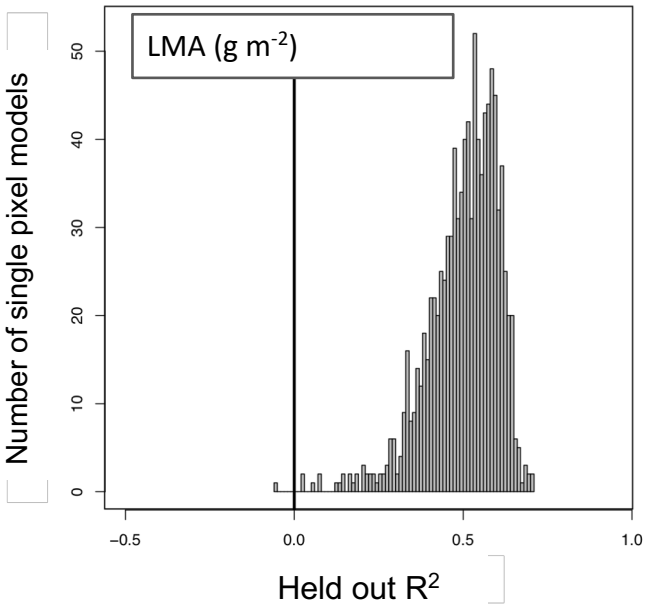
ADVANTAGES OF LABELING PIXELS WITH CROWN IDs

Crown objects?

- Multiple instance approach
- Aggregate predictions to crowns

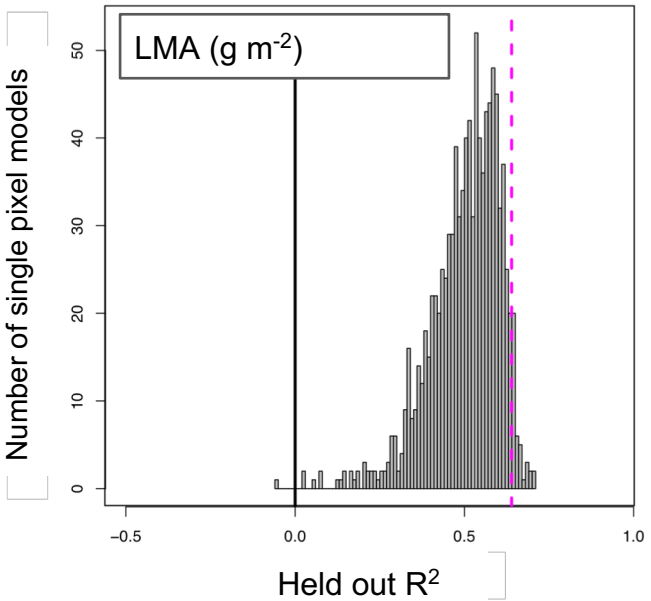


SCALING TO CROWN: ENSEMBLE PERFORMS BETTER THAN PIXEL TRAINED MODELS



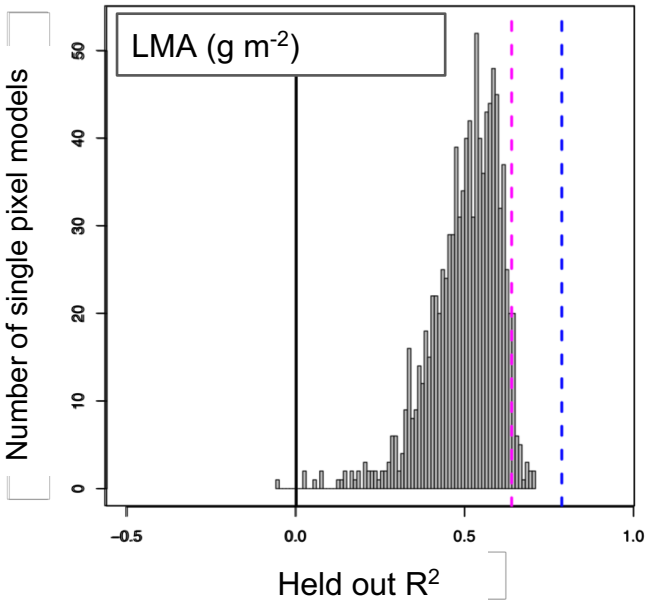
- Distribution of 1000 single models

SCALING TO CROWN: ENSEMBLE PERFORMS BETTER THAN PIXEL TRAINED MODELS



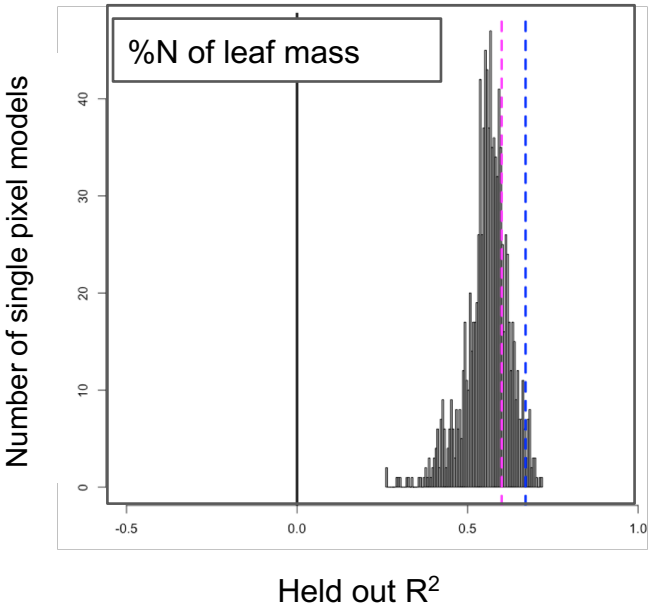
- Distribution of 1000 single models
- Generally outperformed by the ensemble

SCALING TO CROWN: ENSEMBLE PERFORMS BETTER THAN PIXEL TRAINED MODELS



- Distribution of 1000 single models
- Generally outperformed by the ensemble
- Generally outperformed by aggregation at crown scale

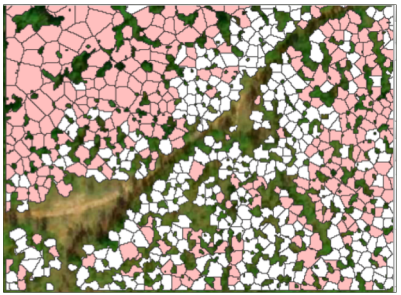
SCALING TO CROWN: ENSEMBLE PERFORMS BETTER THAN PIXEL TRAINED MODELS



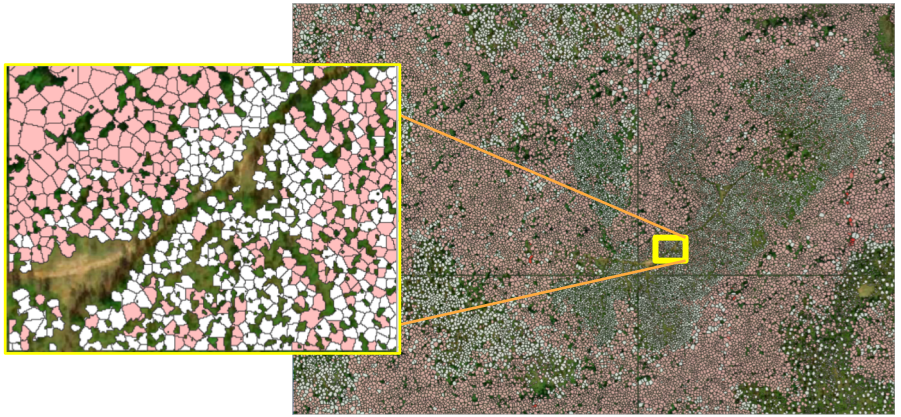
- Distribution of 1000 single models
- Generally outperformed by the ensemble
- Generally outperformed by aggregation at crown scale
- When not, the best models had fairly high AIC or PRESS (a.k.a., we would not have chosen them)

SCALING TO LANDSCAPE

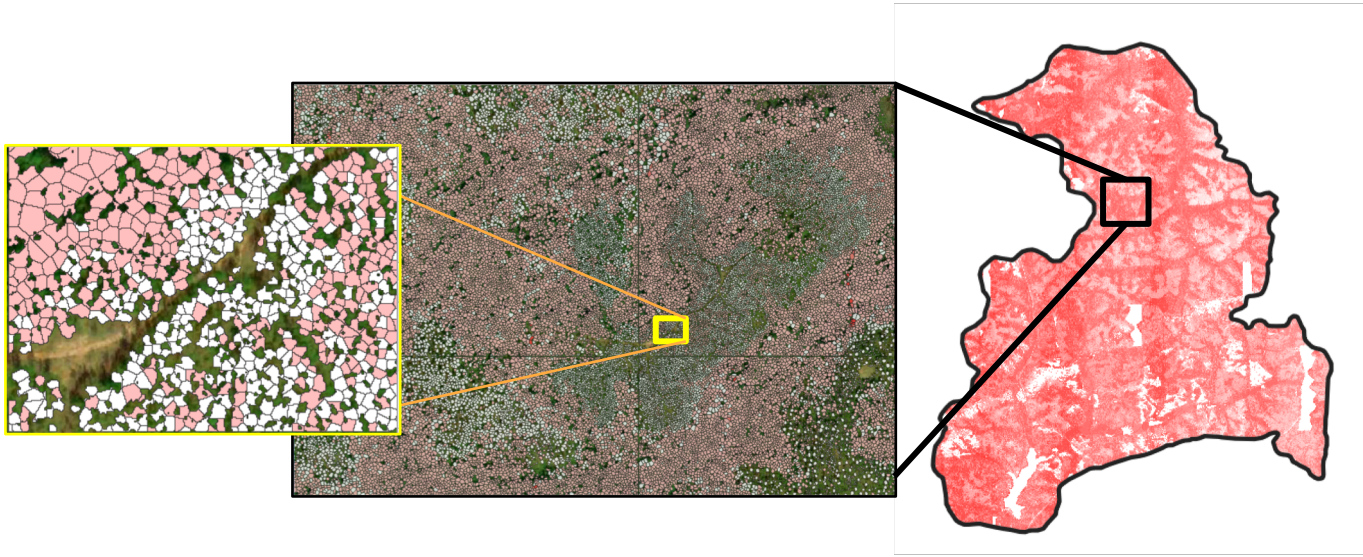
SCALING TO LANDSCAPE



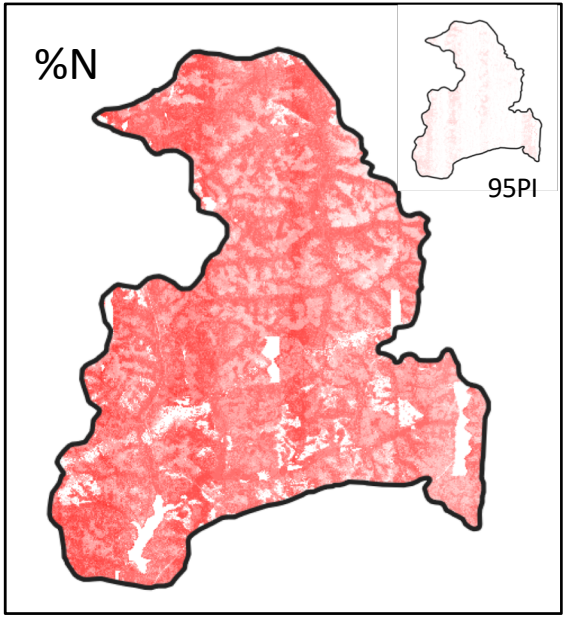
SCALING TO LANDSCAPE

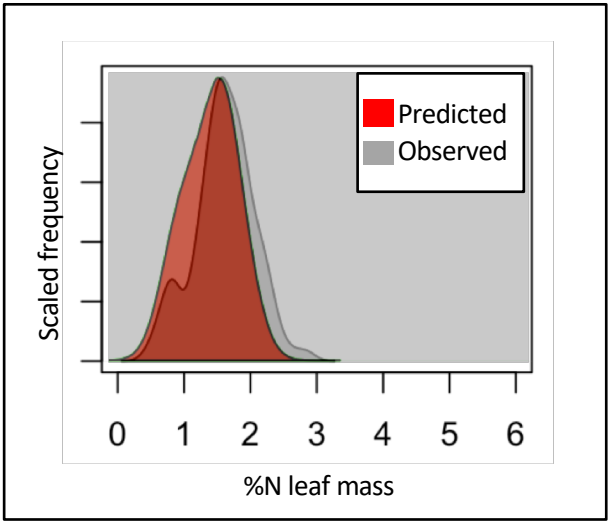


SCALING TO LANDSCAPE

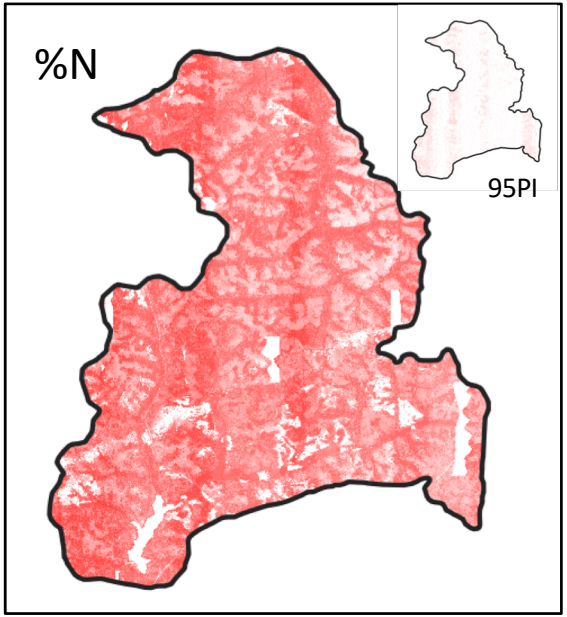


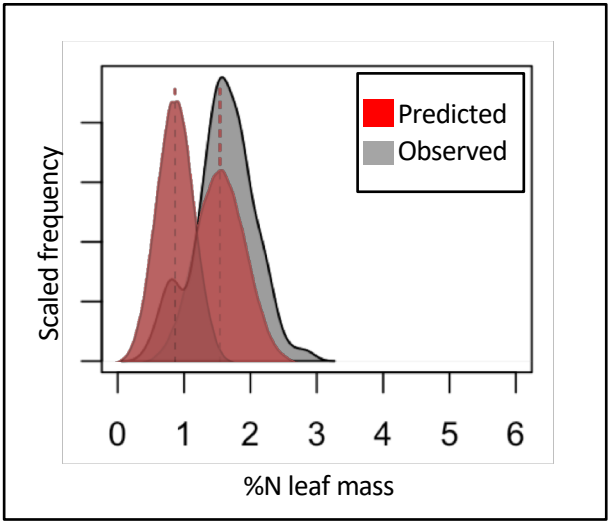
DO THESE MODELS SCALE WELL?



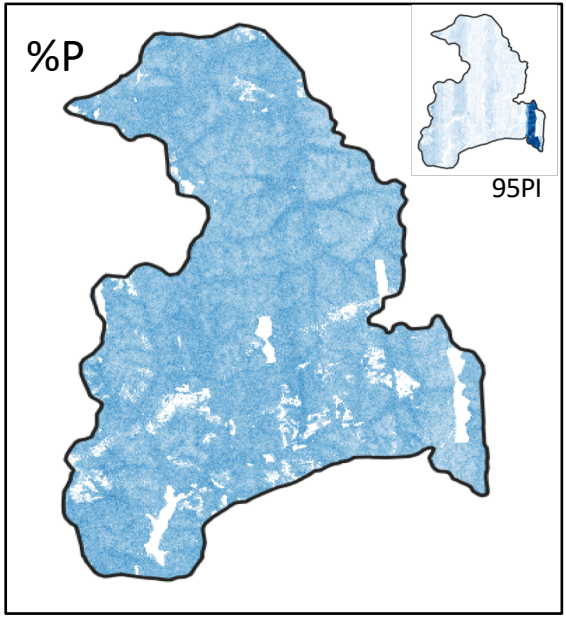


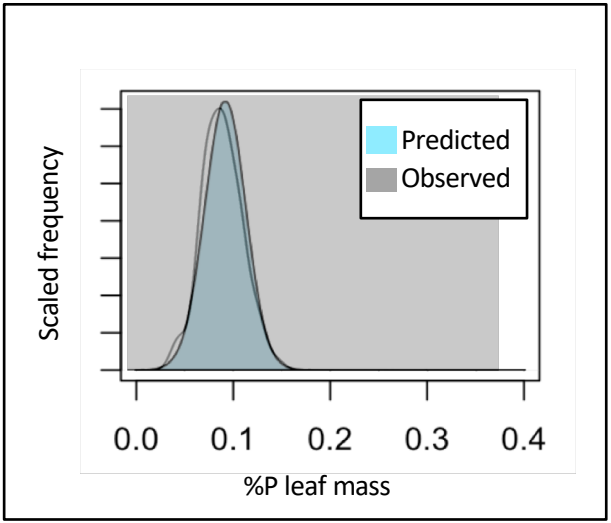
DO THESE MODELS SCALE WELL?





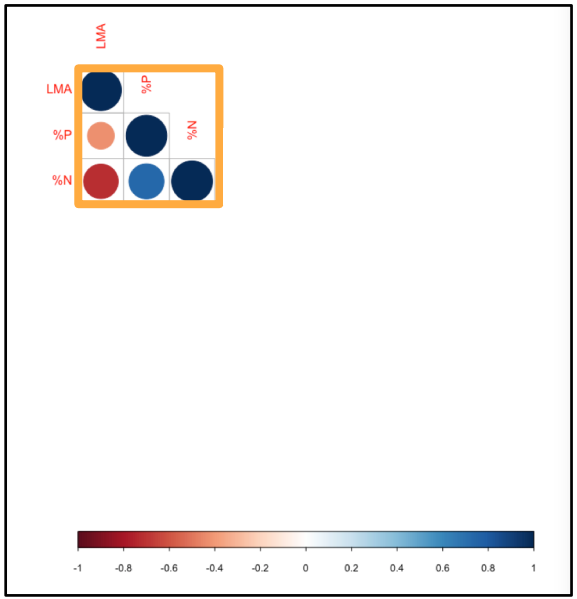
SCALE TO 5 MILLION CROWNS



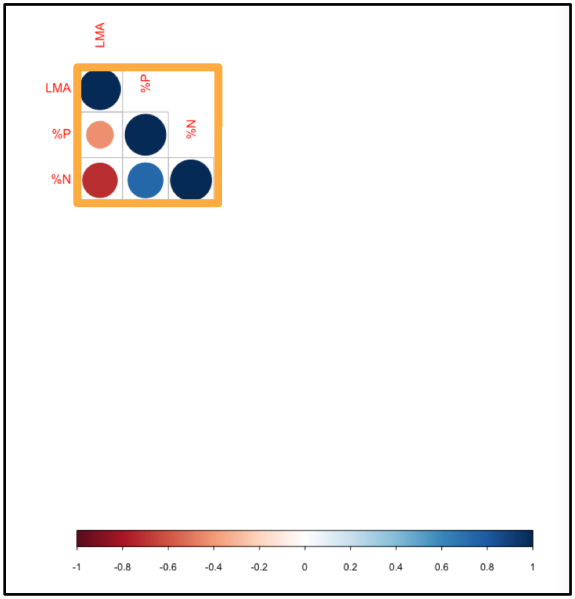


WHAT ARE THE ADVANTAGES OF HAVING PRODUCTS AT THE LEVEL OF TREE CROWNS?

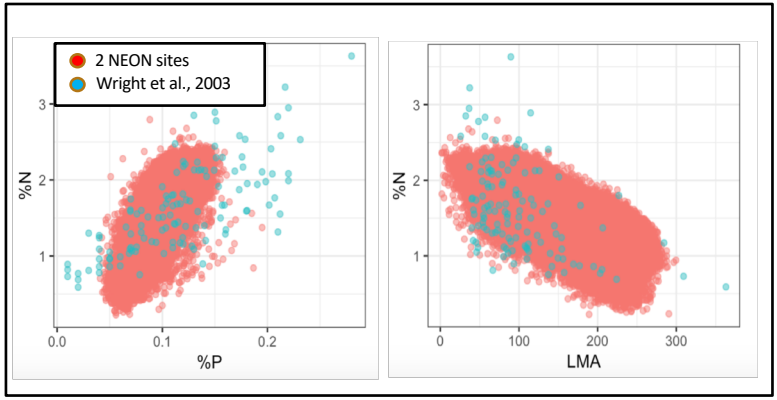
ADVANTAGES OF CROWN BASED PREDICTIONS: PREDICTIONS FUSION



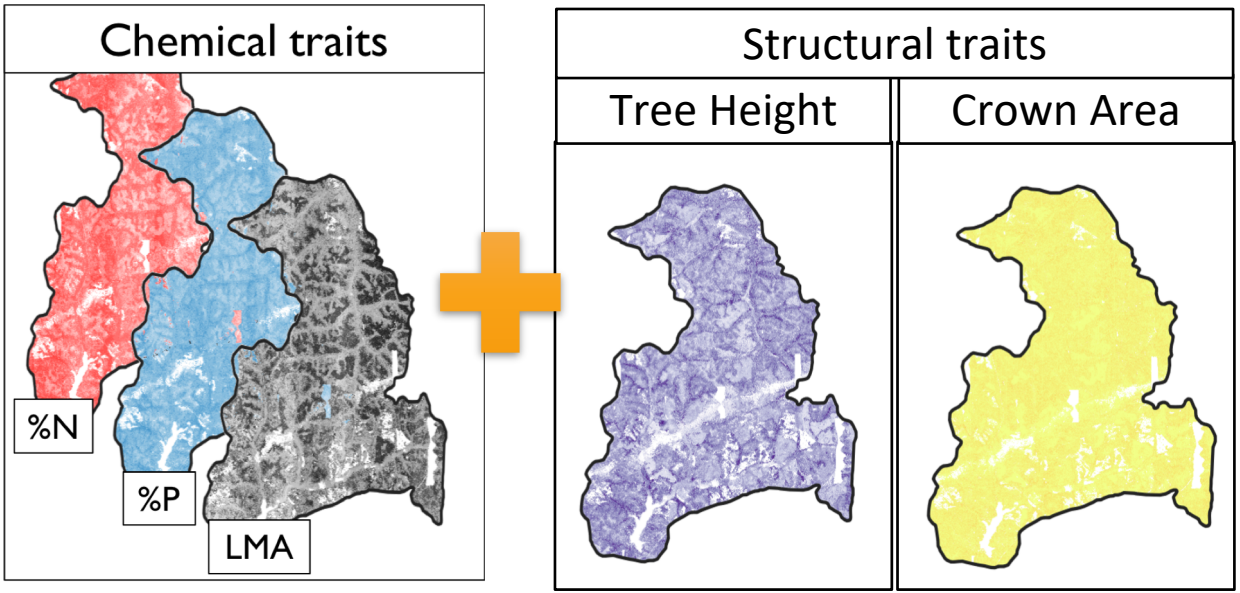
ADVANTAGES OF CROWN BASED PREDICTIONS: DATA FUSION



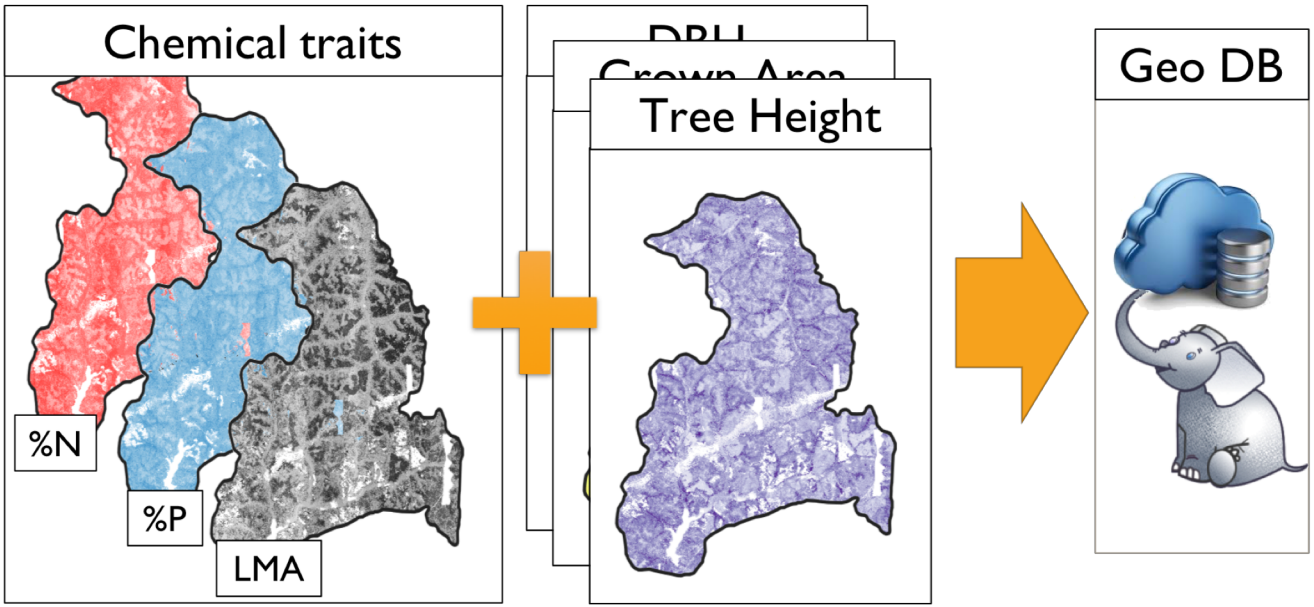
Same fundamental unit of most of the ecological data (such as the Worldwide Leaf Economic Spectrum)



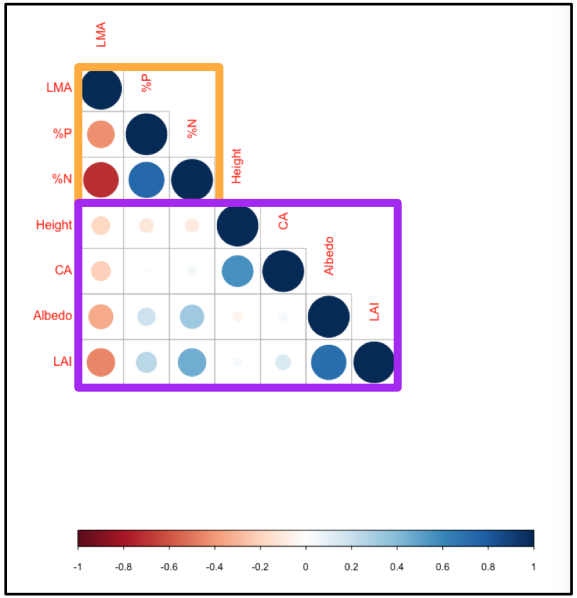
ADVANTAGES OF CROWN BASED PREDICTIONS: PRODUCTS FUSION



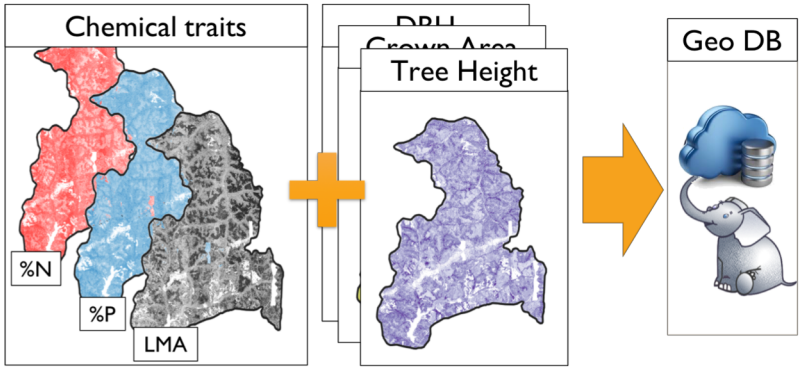
ADVANTAGES OF CROWN BASED PREDICTIONS: DATA FUSION



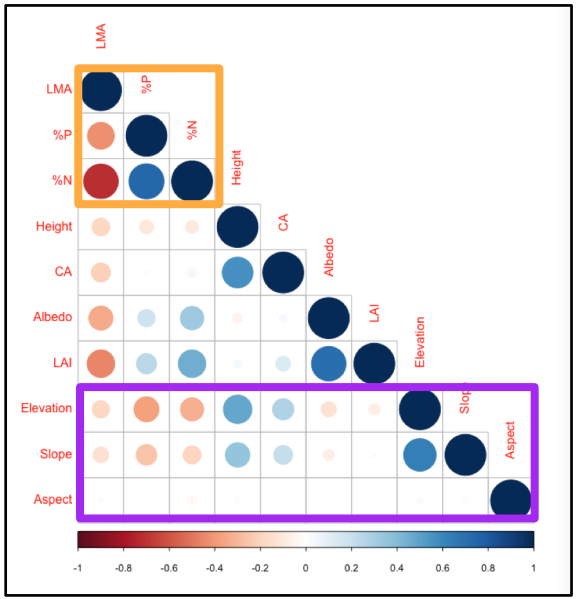
ADVANTAGES OF CROWN BASED PREDICTIONS: PREDICTIONS FUSION



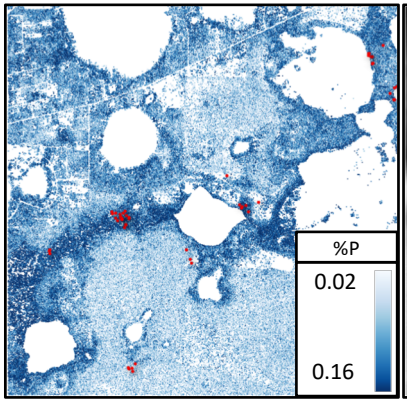
Possible to investigate the relationship between leaf-chemical and plant structural traits

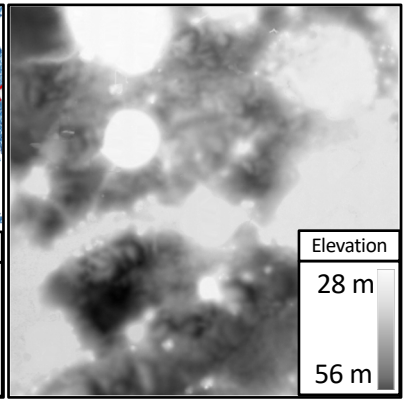


ADVANTAGES OF CROWN BASED PREDICTIONS: SPATIAL EXPLICIT CONTINUOUS DATA



Possible to investigate spatially explicit patterns between leaf-chemical traits and the environment





CONCLUSIONS

We suggest that using crown objects as fundamental unit in remote sensing applications is favorable in:

Advantages in designing prediction models

Multiple instance seems to produce more stable and scalable models

Advantages for doing ecology

Sharing the same fundamental unit simplifies data fusion:

Among inferred data products

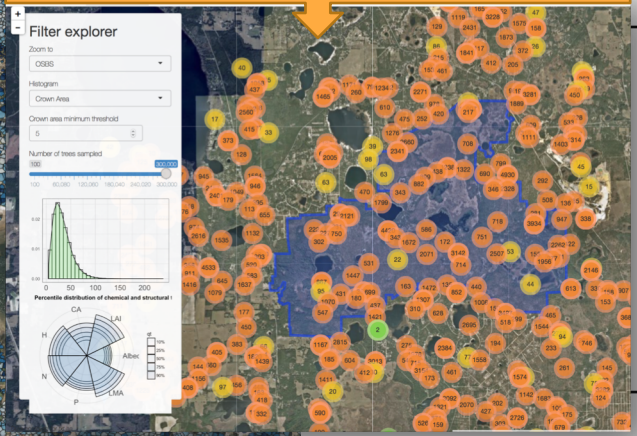
Among datasets at different scales

Thank you for your attention And Thanks to...

- Sarah Graves
- Ethan White
- Stephanie Bohlman
- Jeremy Lichstein
- Aditya Singh
- Ben Weinstein

- The National Ecological Observatory Network
- The University of Florida Biodiversity Institute
- The Gordon and Betty Moore Foundation
- The National Institute of Standards and Technology
- The White and Ernest labs all!

Explore and download the data soon!



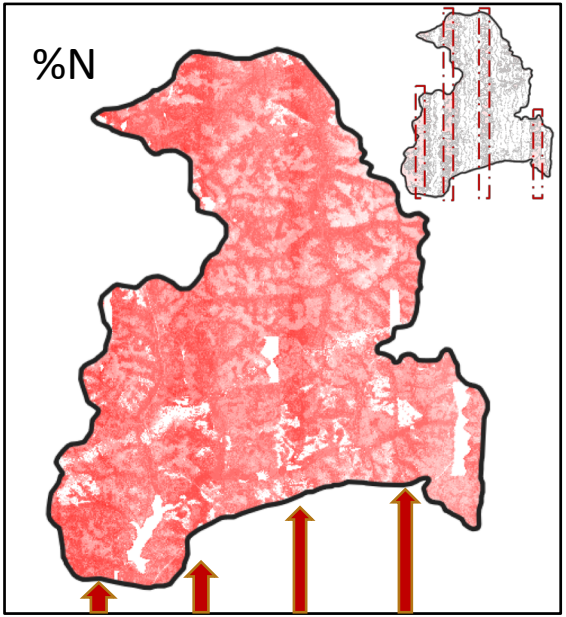
Sergio Marconi,
PhD student, WEecology (White's Lab)
School of Natural Resources and Environment (SNRE)

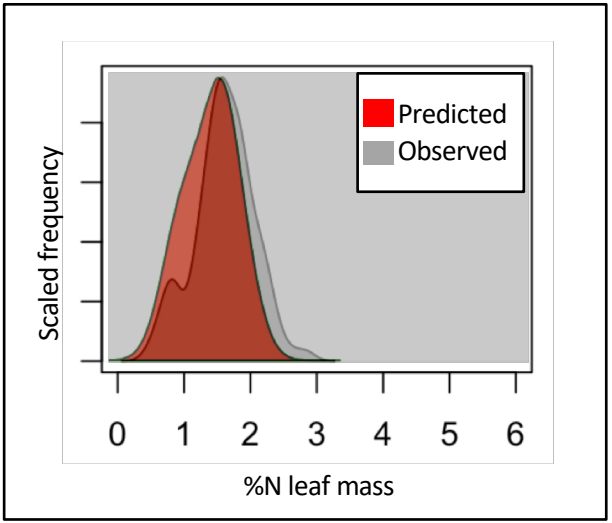
sergio.marconi@weecology.org

@MarconiS

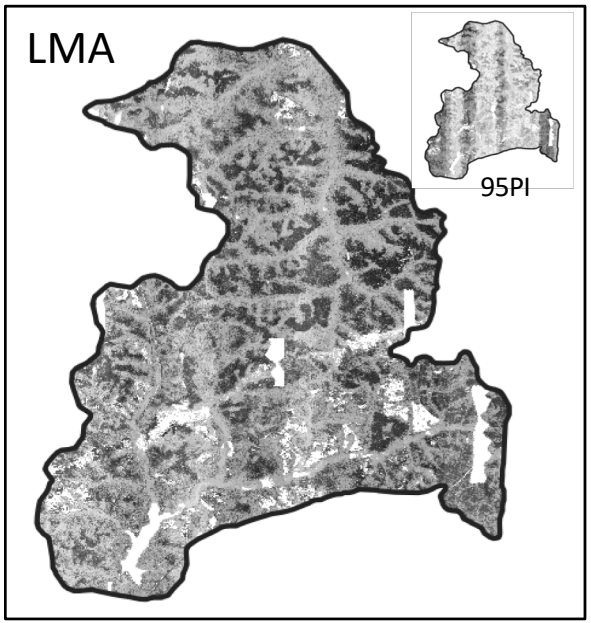
@Sergio_marconi

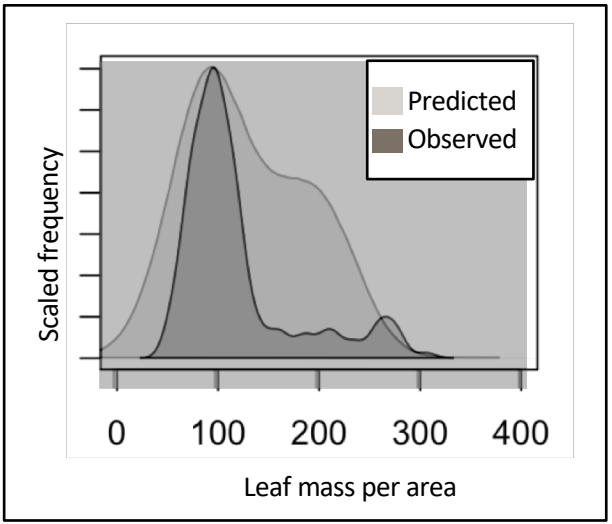
UNCERTAINTY MATTERS



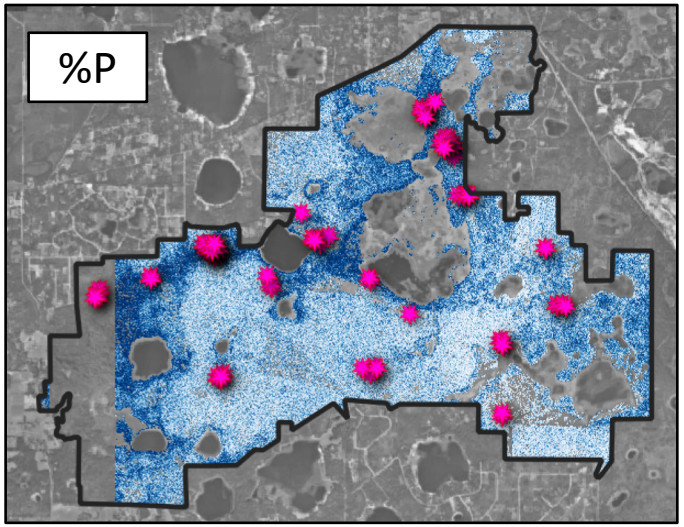


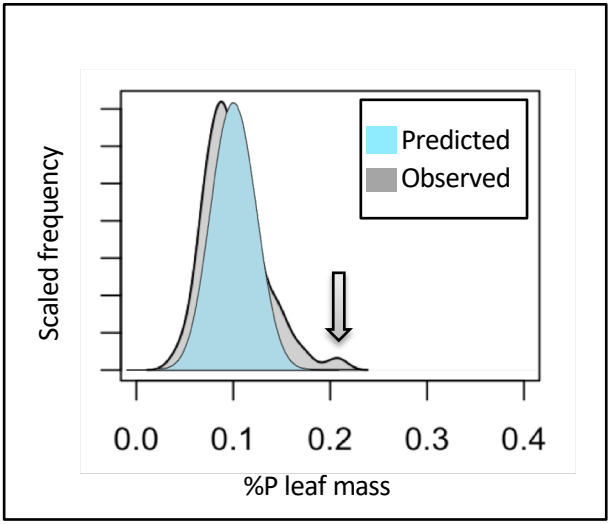
SCALE TO 5 MILLION CROWNS

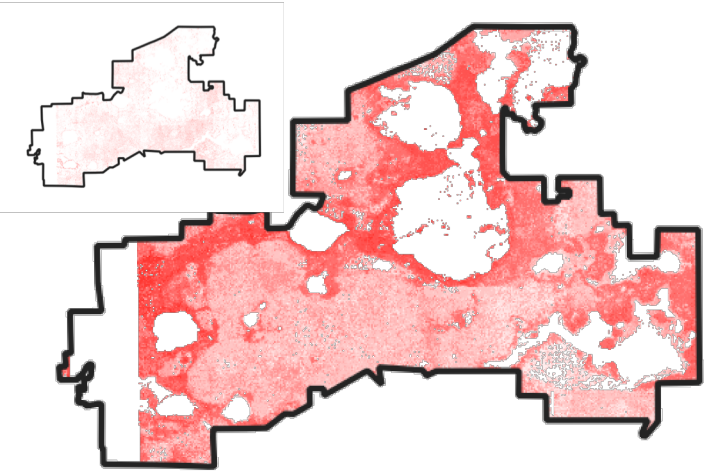


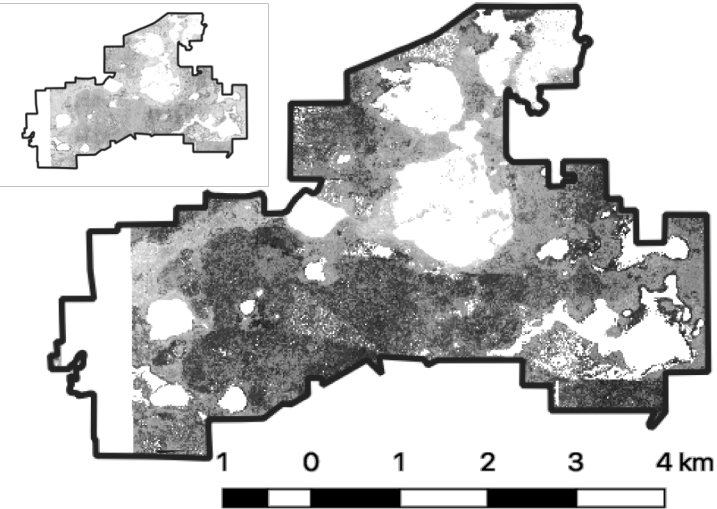


SCALE TO 5 MILLION CROWNS

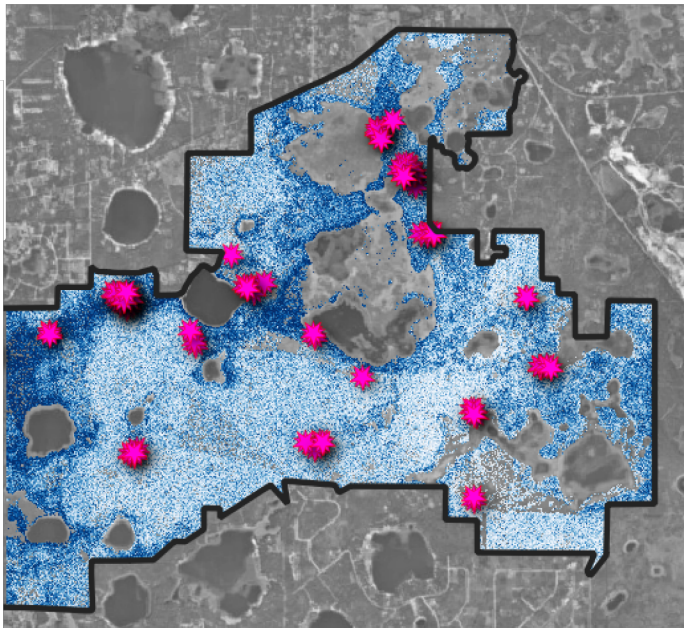




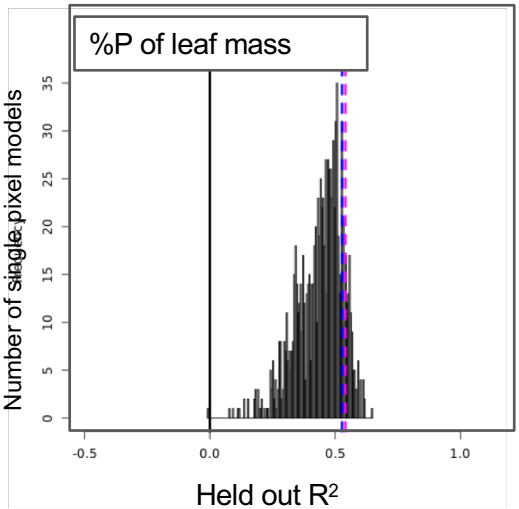




OSBS



SCALING TO CROWN: ENSEMBLE PERFORMS BETTER THAN PIXEL TRAINED MODELS



- Similar results for all the traits modeled
- Models outperforming ensemble ranked low in
- validation (both PRESS and AIC)

SPECTRAL MIXTURE: MAYBE AN OPPORTUNITY TO LINK NEON AND NASA