



# Scaling forest diversity across space and time in a non-equilibrial world

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John Grady (Washington University in St. Louis) & Noah Charney (U. Maine)

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# Forest structure influences habitat quality for many wildlife species



# Forest structure influences habitat quality for many wildlife species

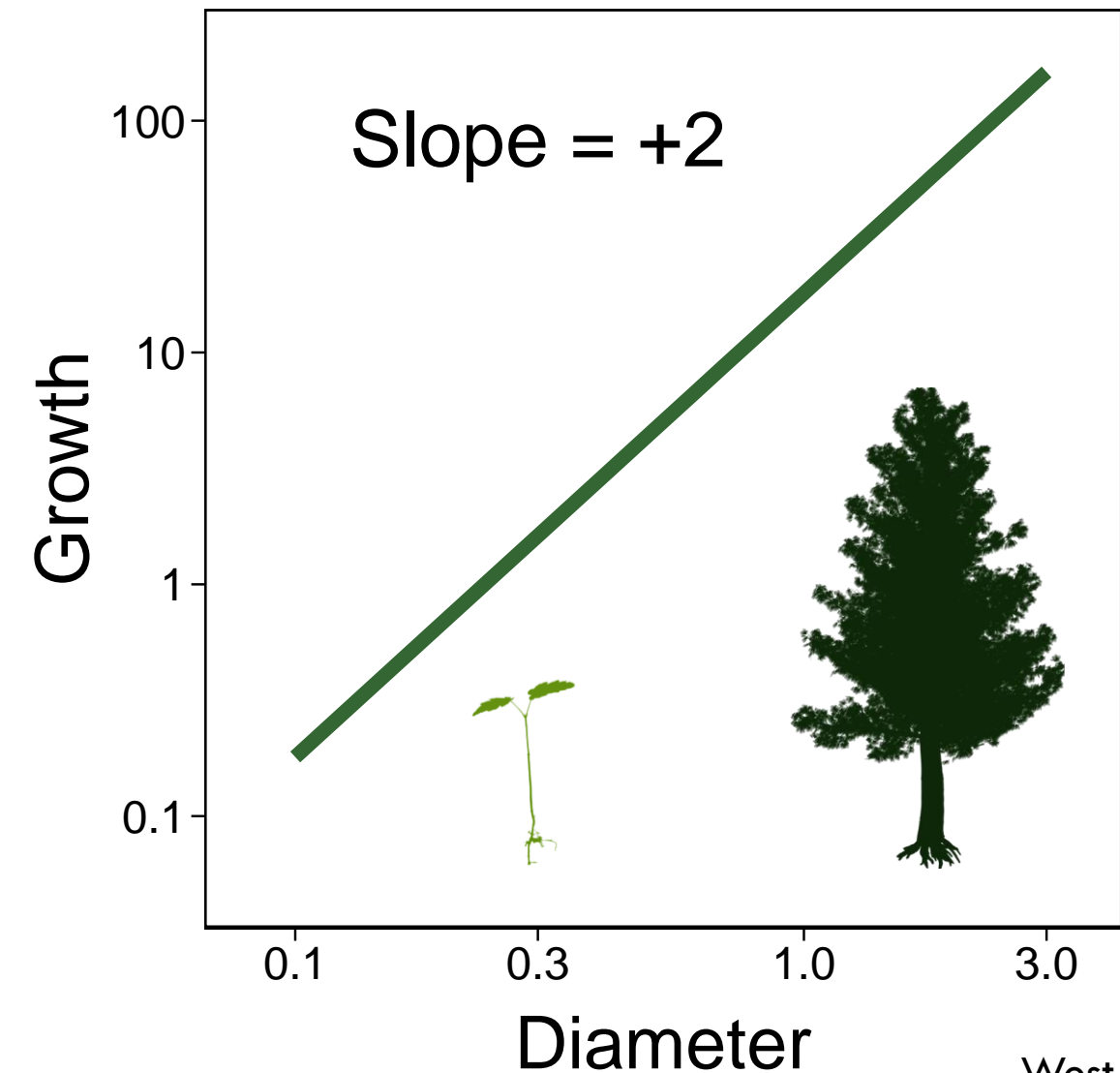


# Challenges to understanding understory vegetation structure from remotely sensed data

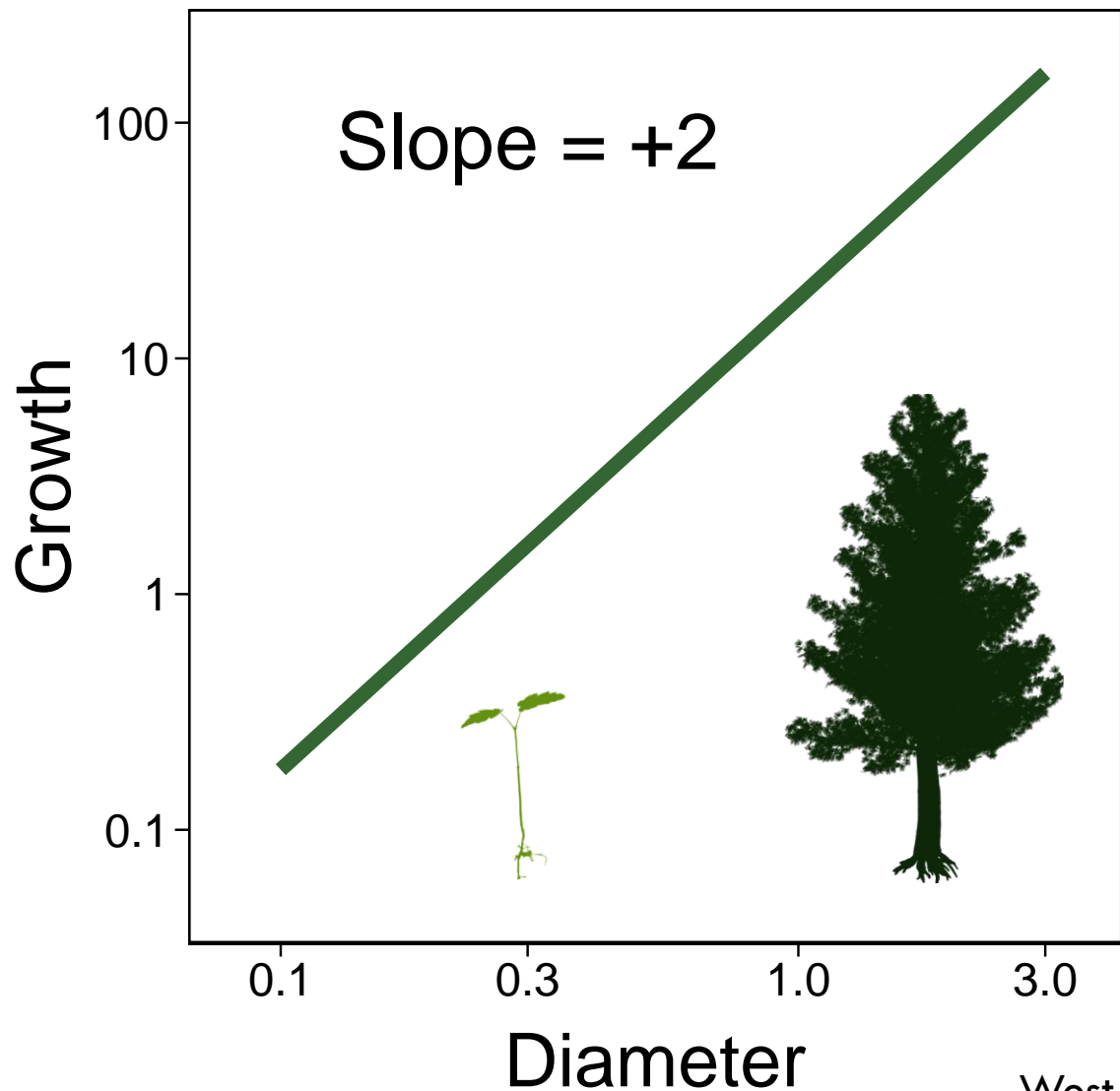


Can ecological theory improve predictions of understory vegetation structure from remotely sensed data?

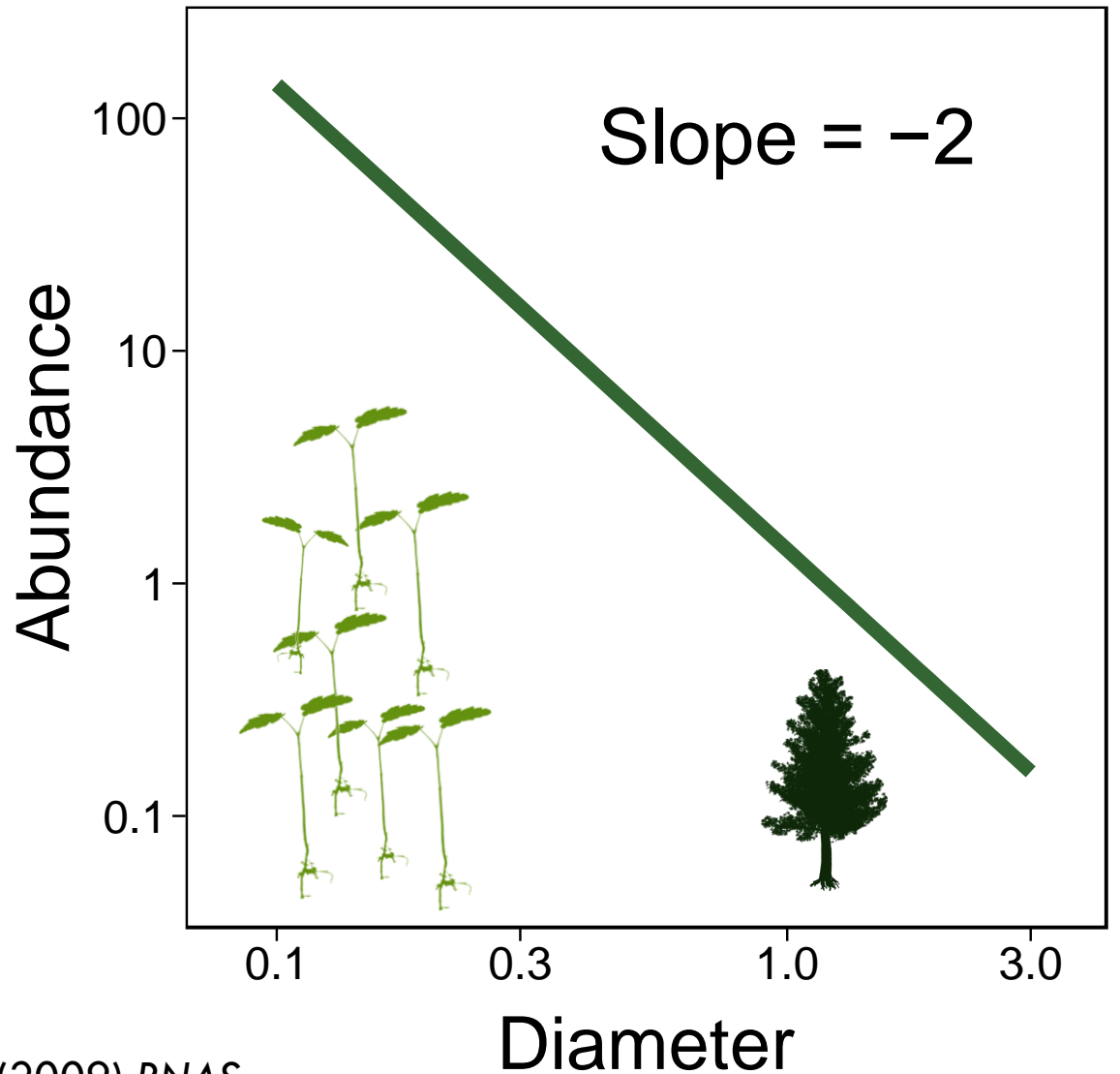
# Metabolic scaling theory: general rules about growth, size, & abundance relationships



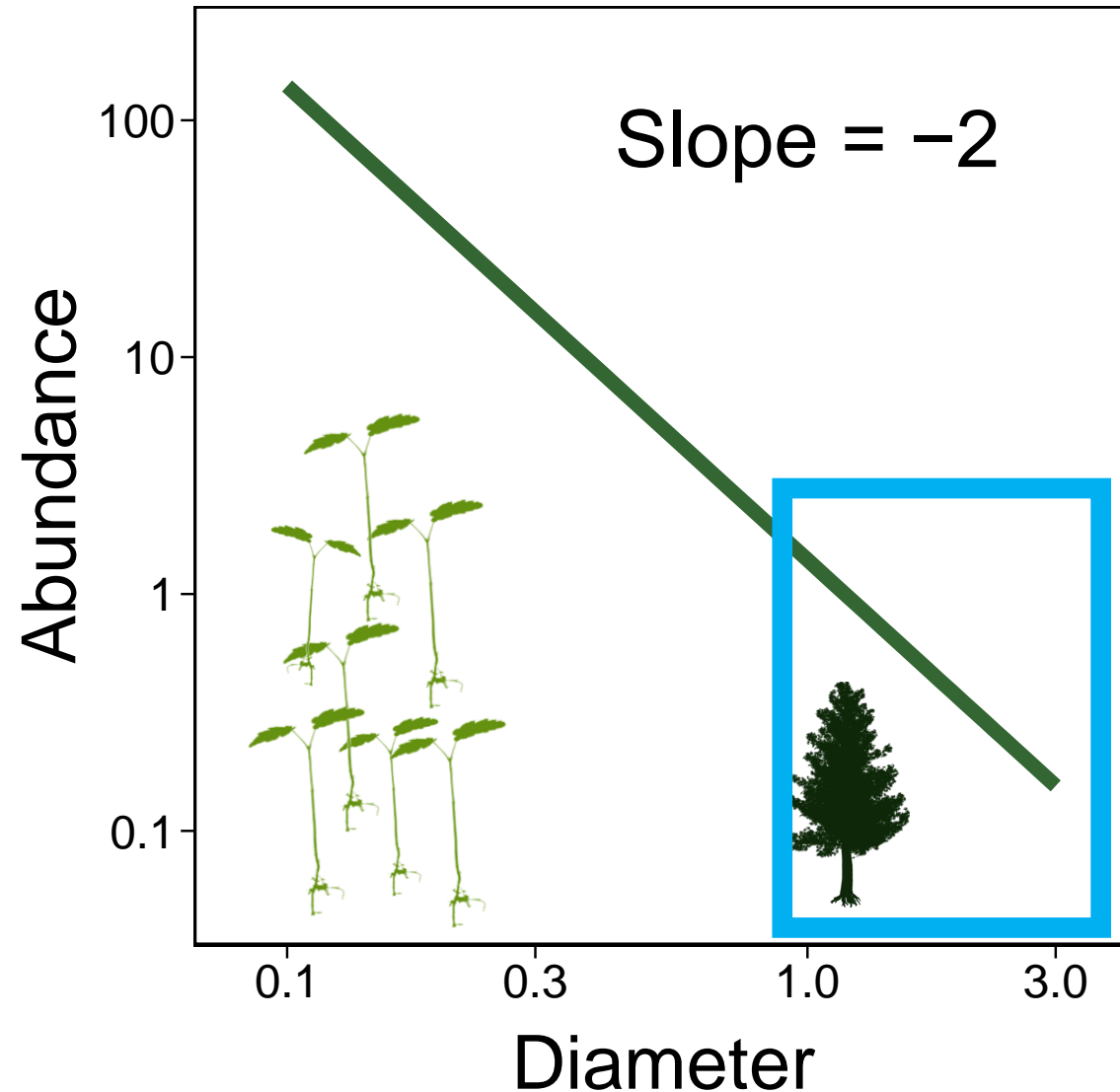
# Metabolic scaling theory: general rules about growth, size, & abundance relationships



West et al. (2009) *PNAS*



Can ecological theory improve predictions of understory vegetation structure from remotely sensed data?





However, this theory  
ignores functional  
difference between species

Journal of Ecology



Special Feature: The Tree of Life in Ecosystems – Forum | [Free Access](#)

The world-wide ‘fast–slow’ plant economics spectrum: a traits manifesto

Peter B. Reich 

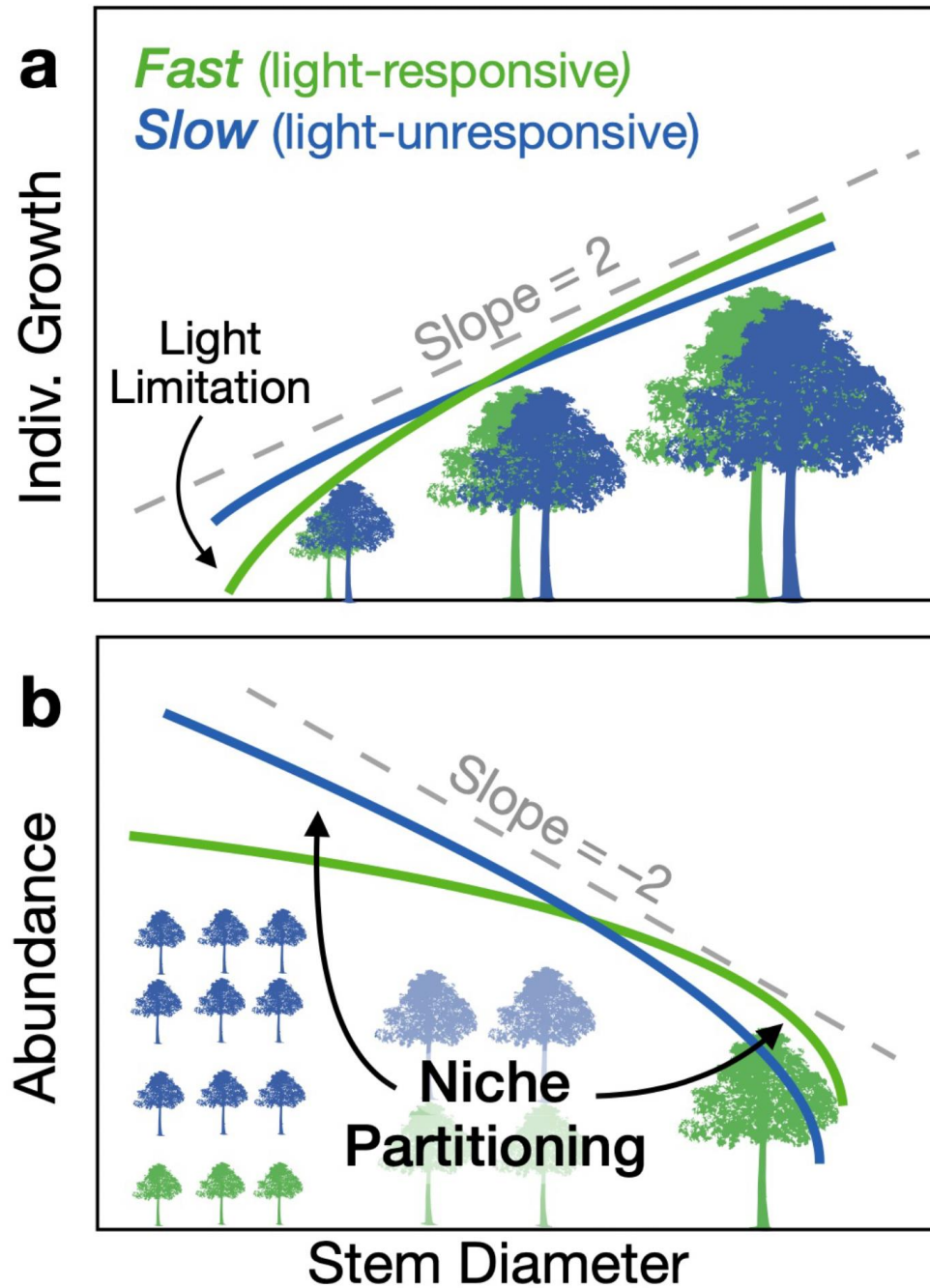
First published: 19 February 2014 | <https://doi.org/10.1111/1365-2745.12211> | Citations: 1,579

A photograph of a forest with tall, thin trees and a dense canopy of green leaves. Sunlight filters through the trees, creating dappled light on the forest floor. The text 'Live slow, Die old' is overlaid in white at the top of the image.

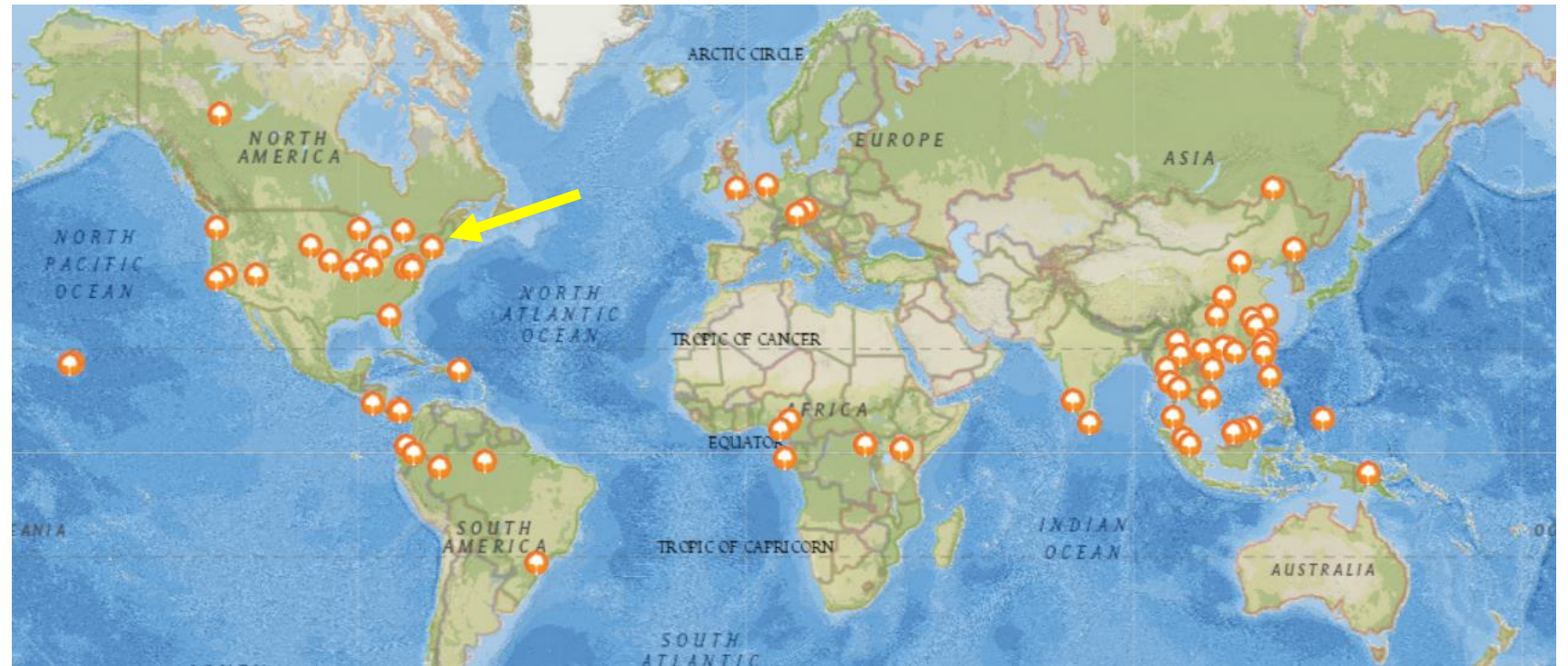
Live slow, Die old

Live fast, Die young

Predictions of theory incorporating fast-slow life histories



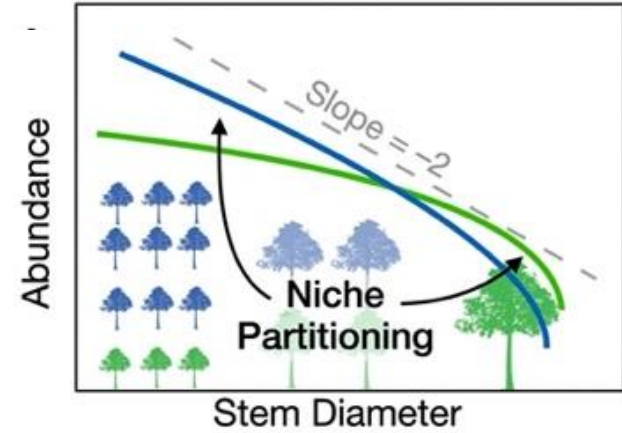
# Exploring predictions at Harvard Forest



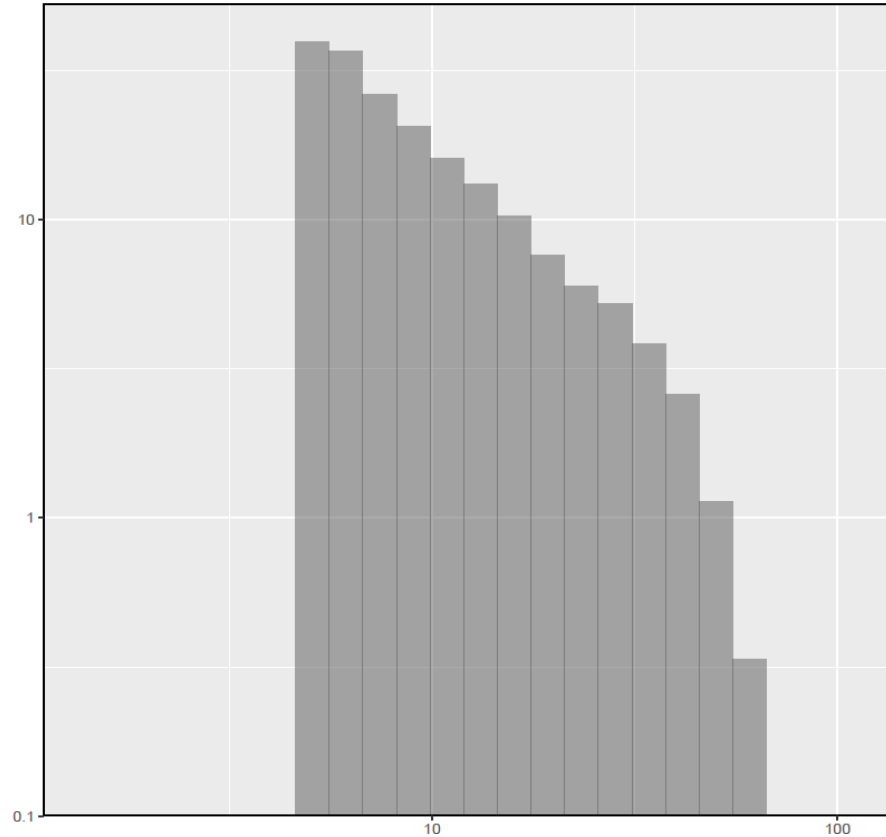
# Exploring predictions at Harvard Forest



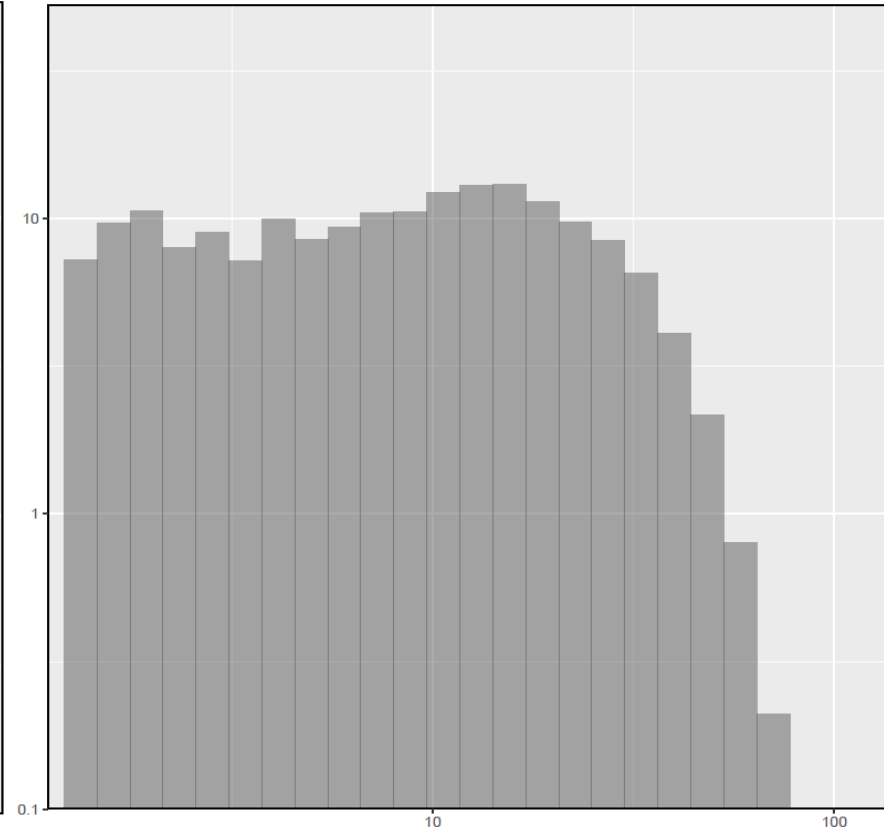
# Exploring predictions at Harvard Forest



'Slow'  
Late Successional

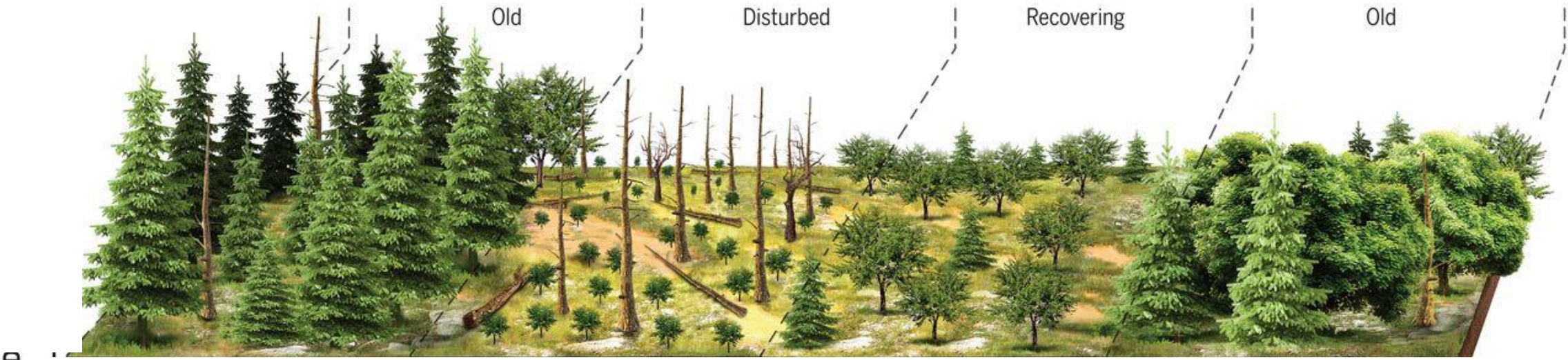


'Fast'  
Mid-Successional

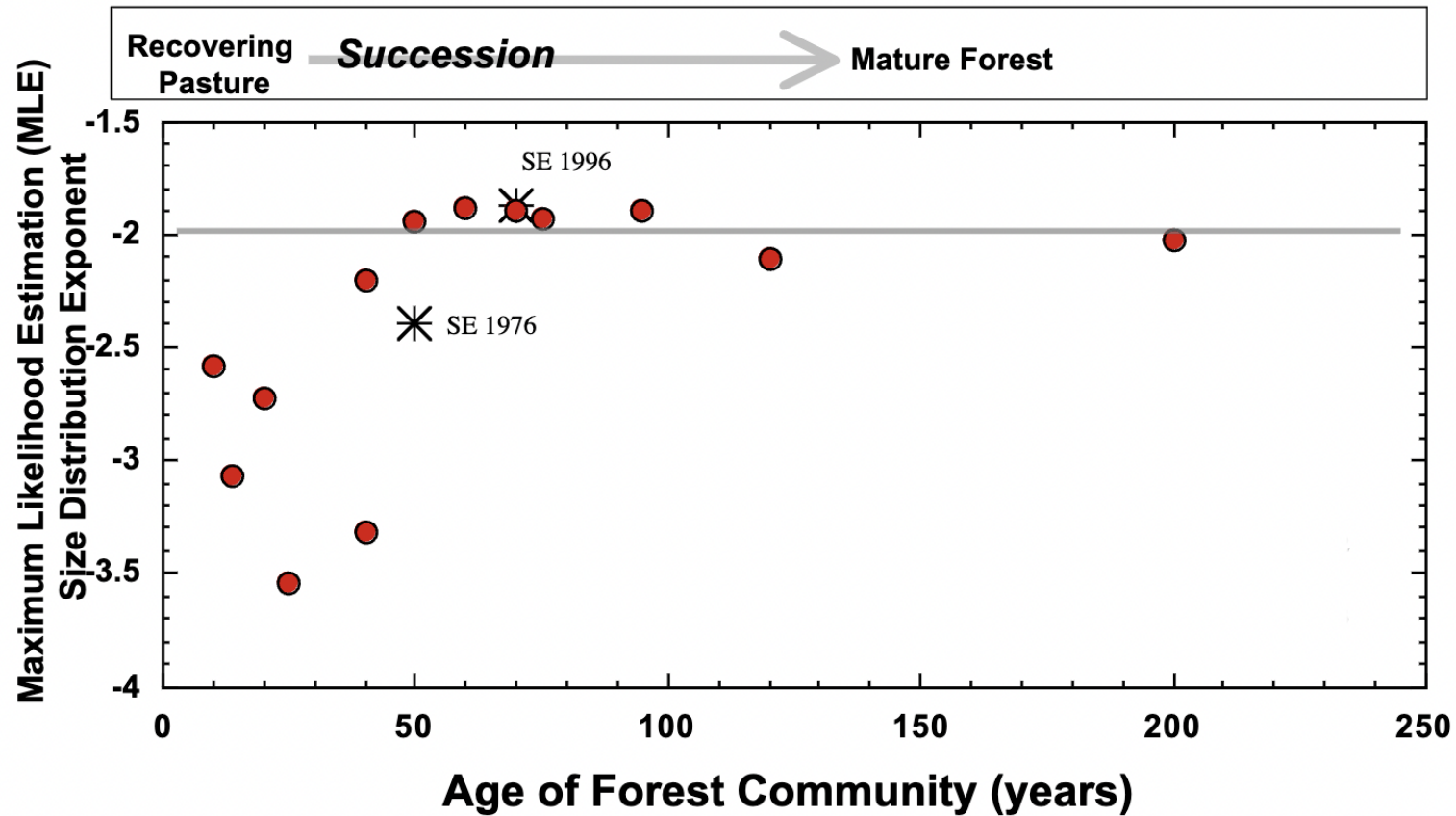


Diameter

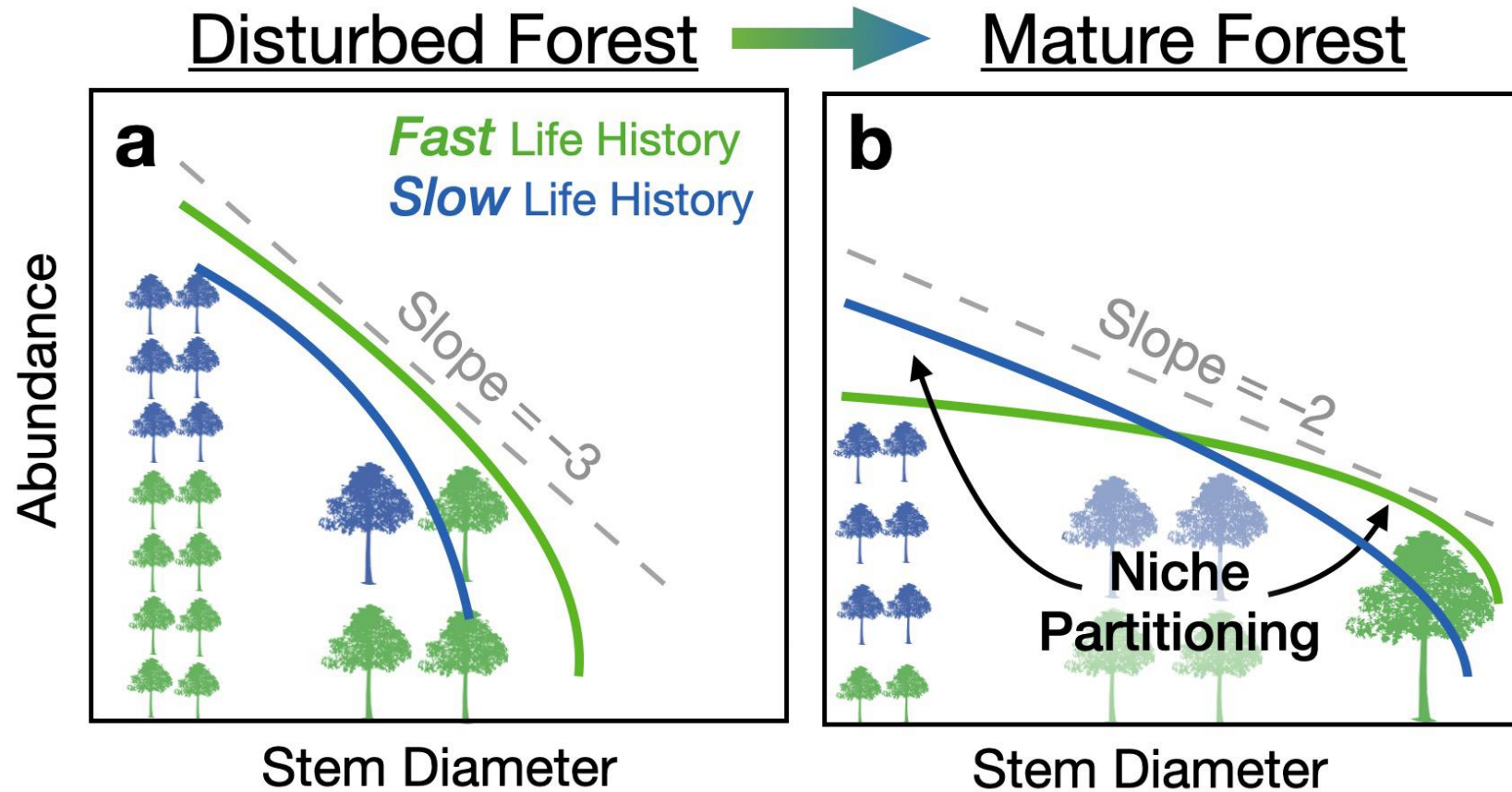
Also, this theory assumes equilibril conditions



# Successional convergence to MST



# Prediction: Disturbance generates predictable deviations from Metabolic Scaling Theory





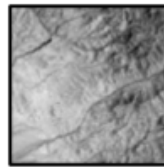
# Objective: Spatio-temporal modeling of forest structure

In situ data across time



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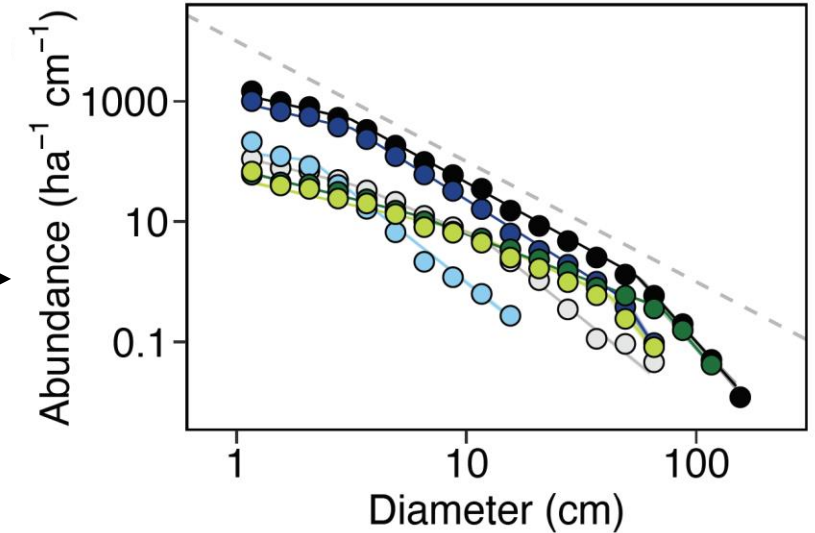
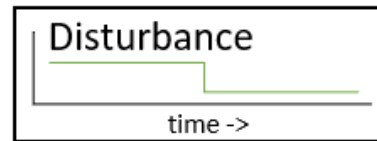
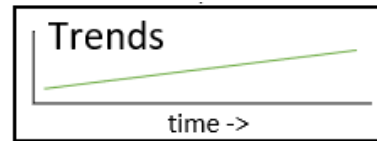
Static & Dynamic Remotely Sensed data



- Elevation
- sd(elev)
- other metrics



- Geologic types
- Shannon entropy
- other metrics



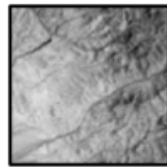
# Spatio-temporal modeling of forest structure

In situ data across time



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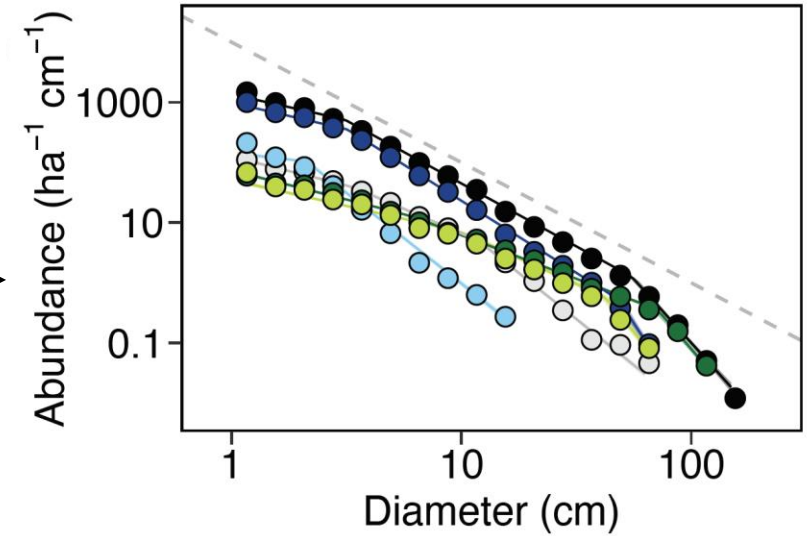
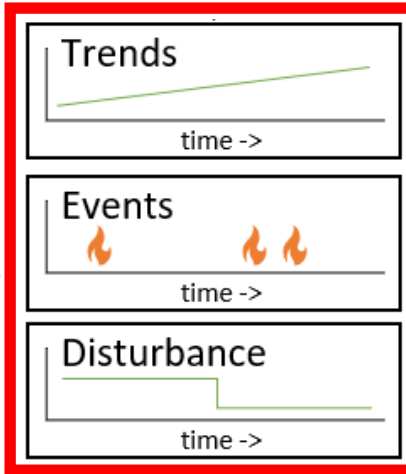
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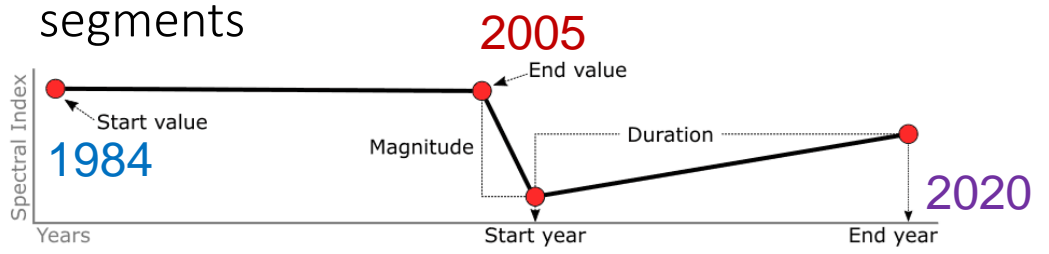


Landsat

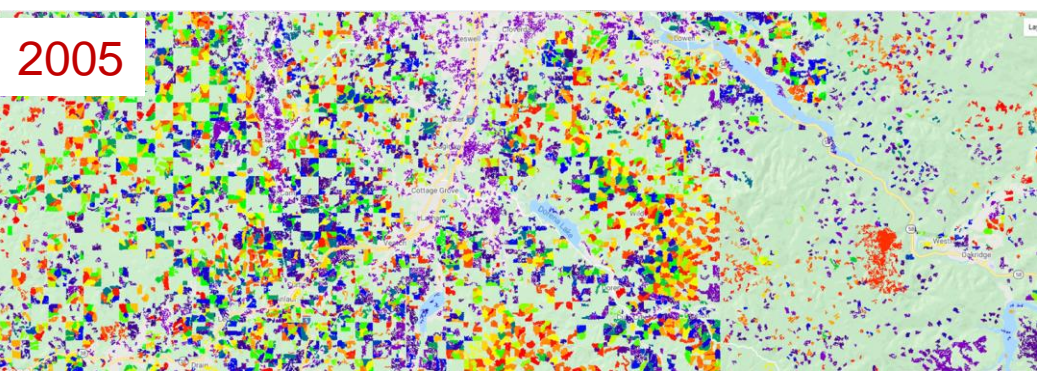
Data pre-processing  
LandTrendr for Google  
Earth Engine



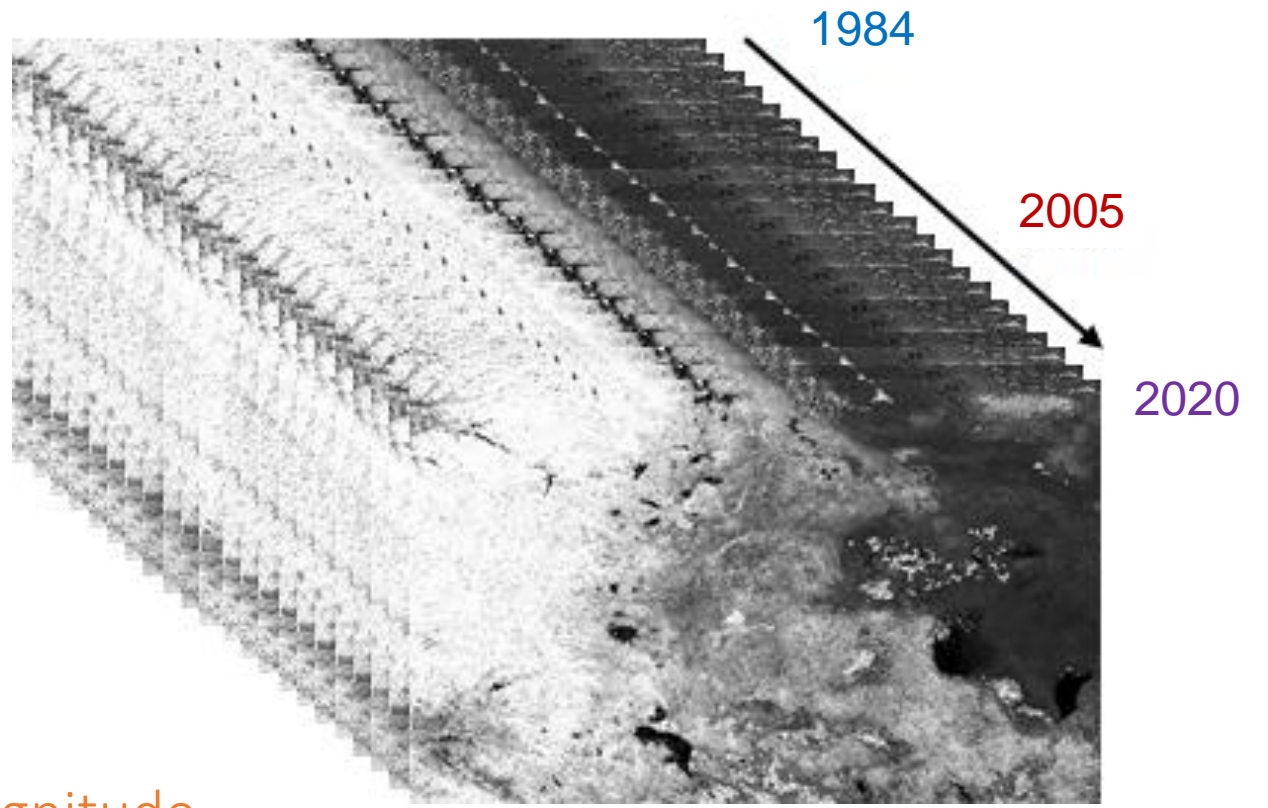
Each 30-m pixel timeseries broken into  
segments



E.g.: start year of segment with greatest vegetation loss



Disturbance

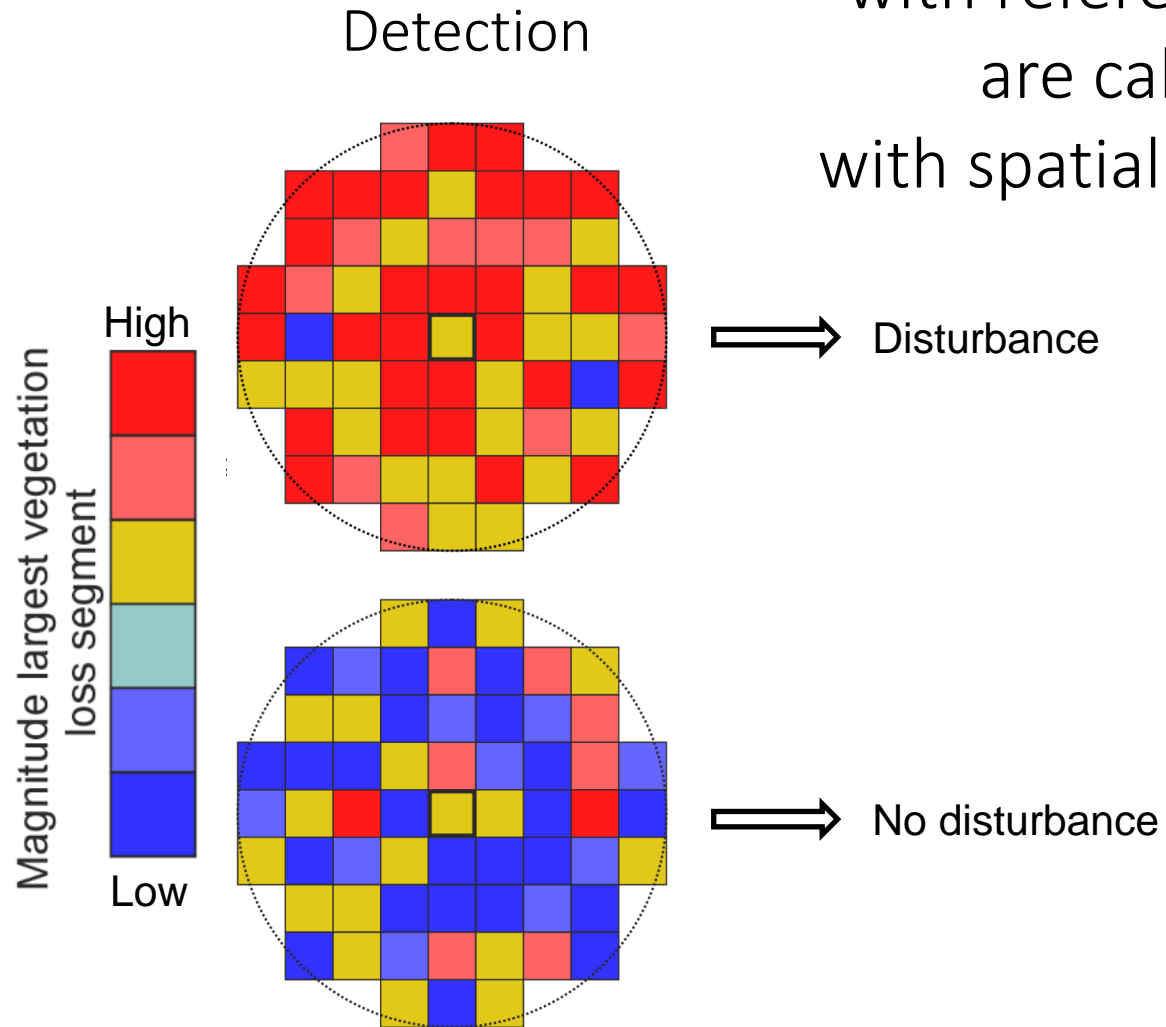


magnitude,  
rate, &  
duration of change





2 Random Forest models  
with reference points\*  
are calibrated  
with spatial information:



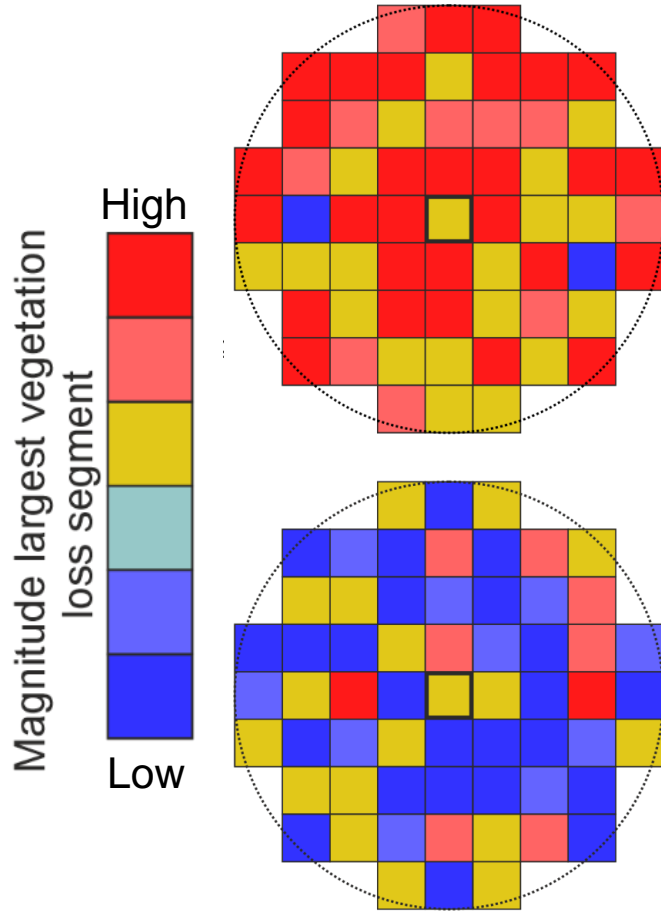
\*25,000 reference points across CONUS (1985-2020)





2 Random Forest models with reference points\* are calibrated with spatial information:

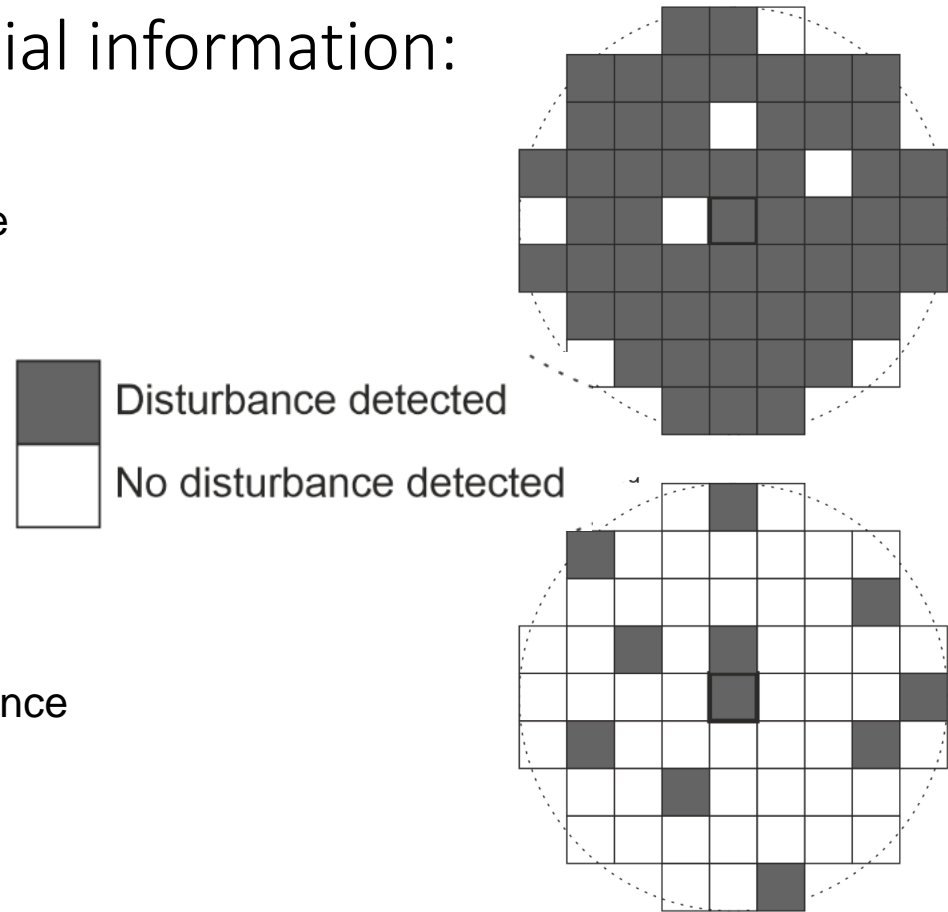
Detection



⇒ Disturbance

⇒ No disturbance

Attribution



⇒ Clearcut

⇒ Biotic

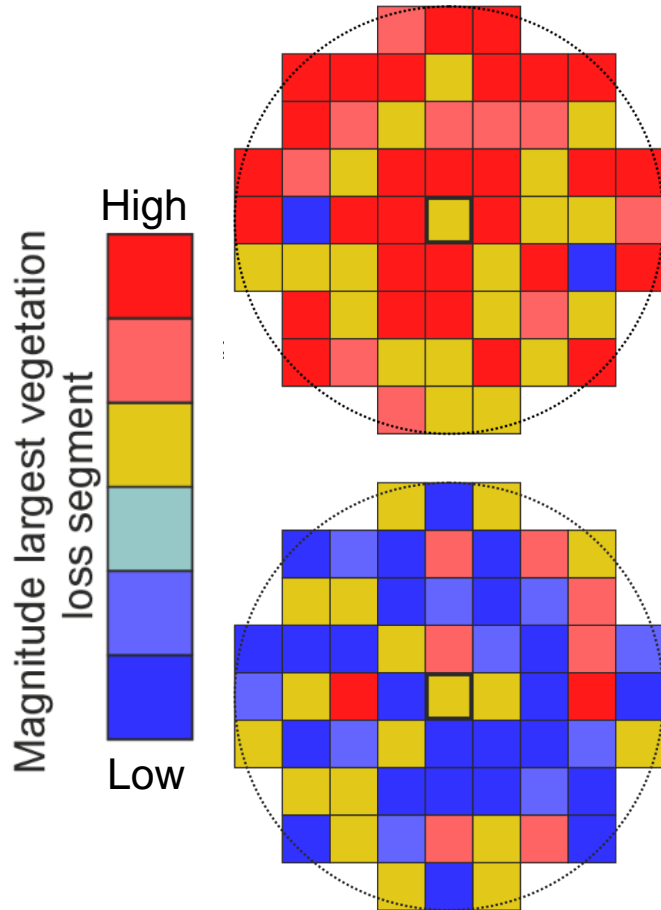
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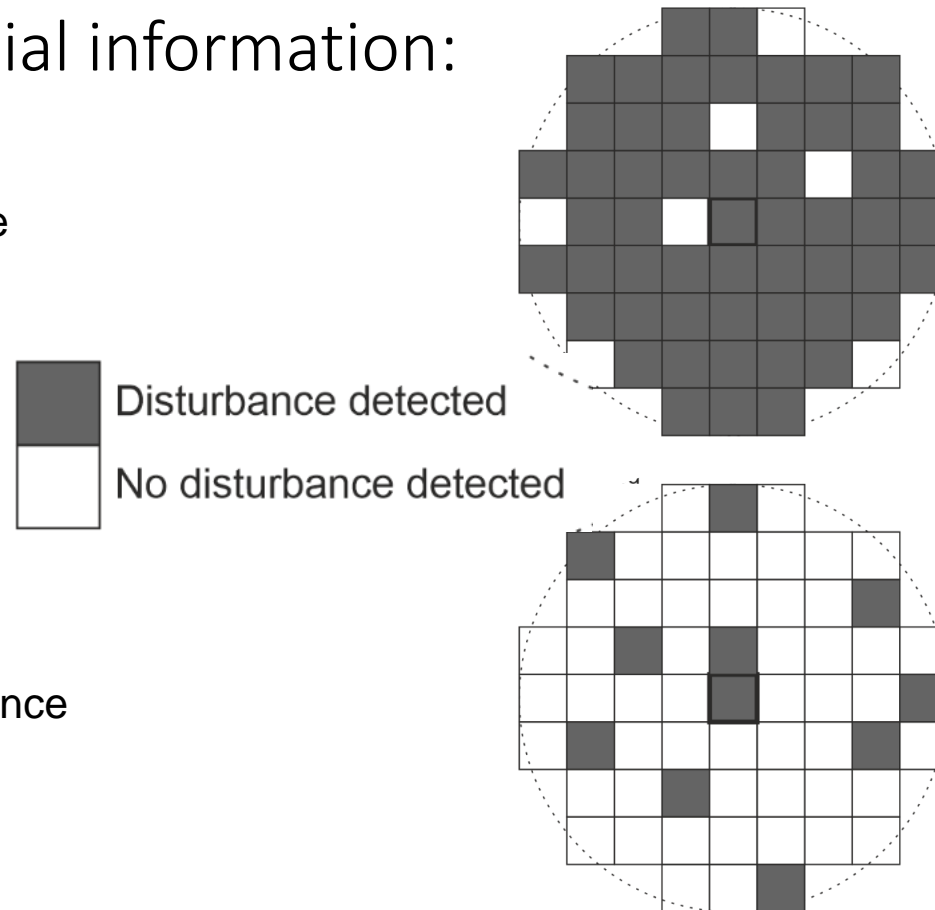
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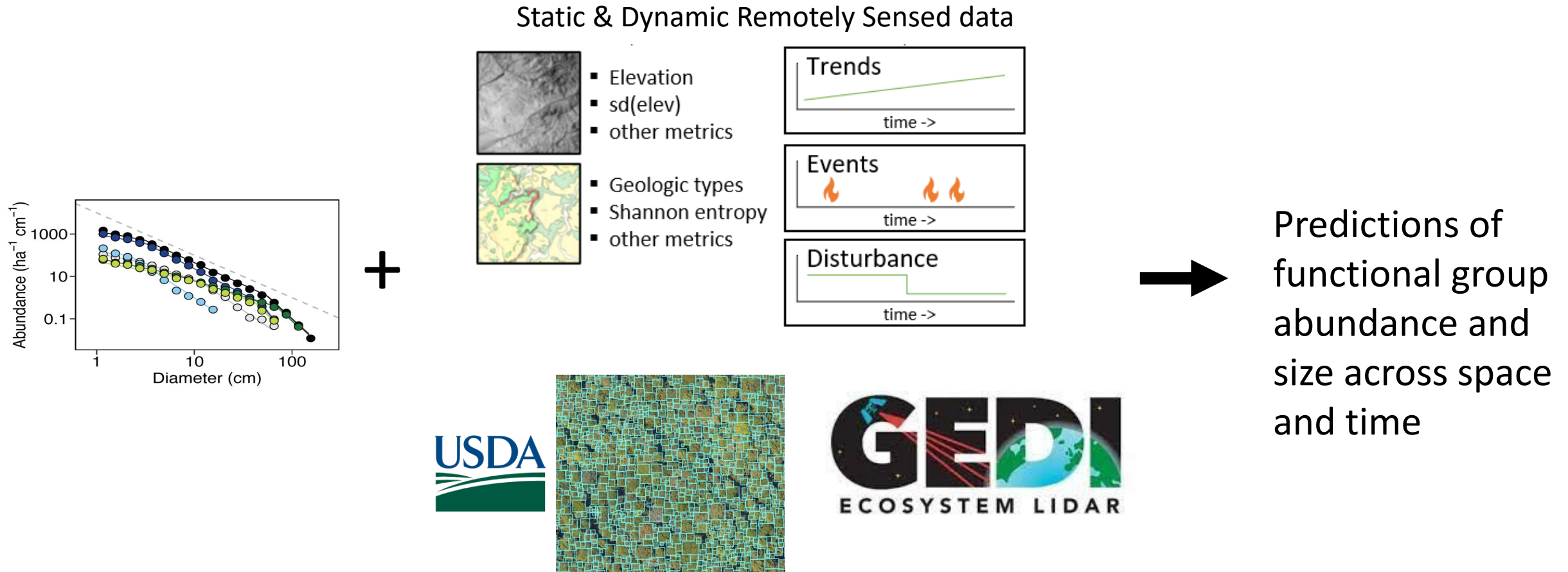
⇒ Biotic

\*25,000 reference points across CONUS (1985-2020)

End Result: wall-to-wall 30-m CONUS map of disturbance variables & disturbance type (each year 1985-2020)



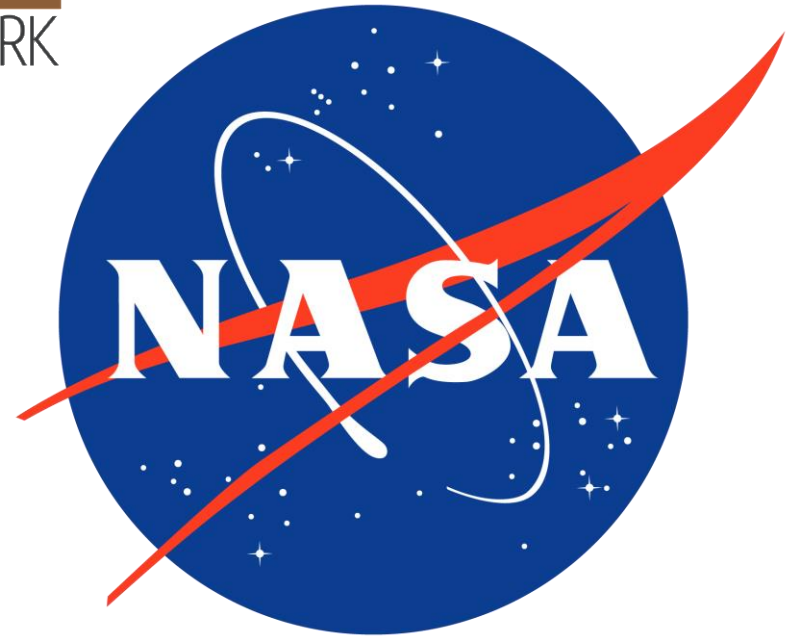
# *Future directions: Using RS data and models to make predictions across space and time*



Thank you!



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20-BIODIV20-0024

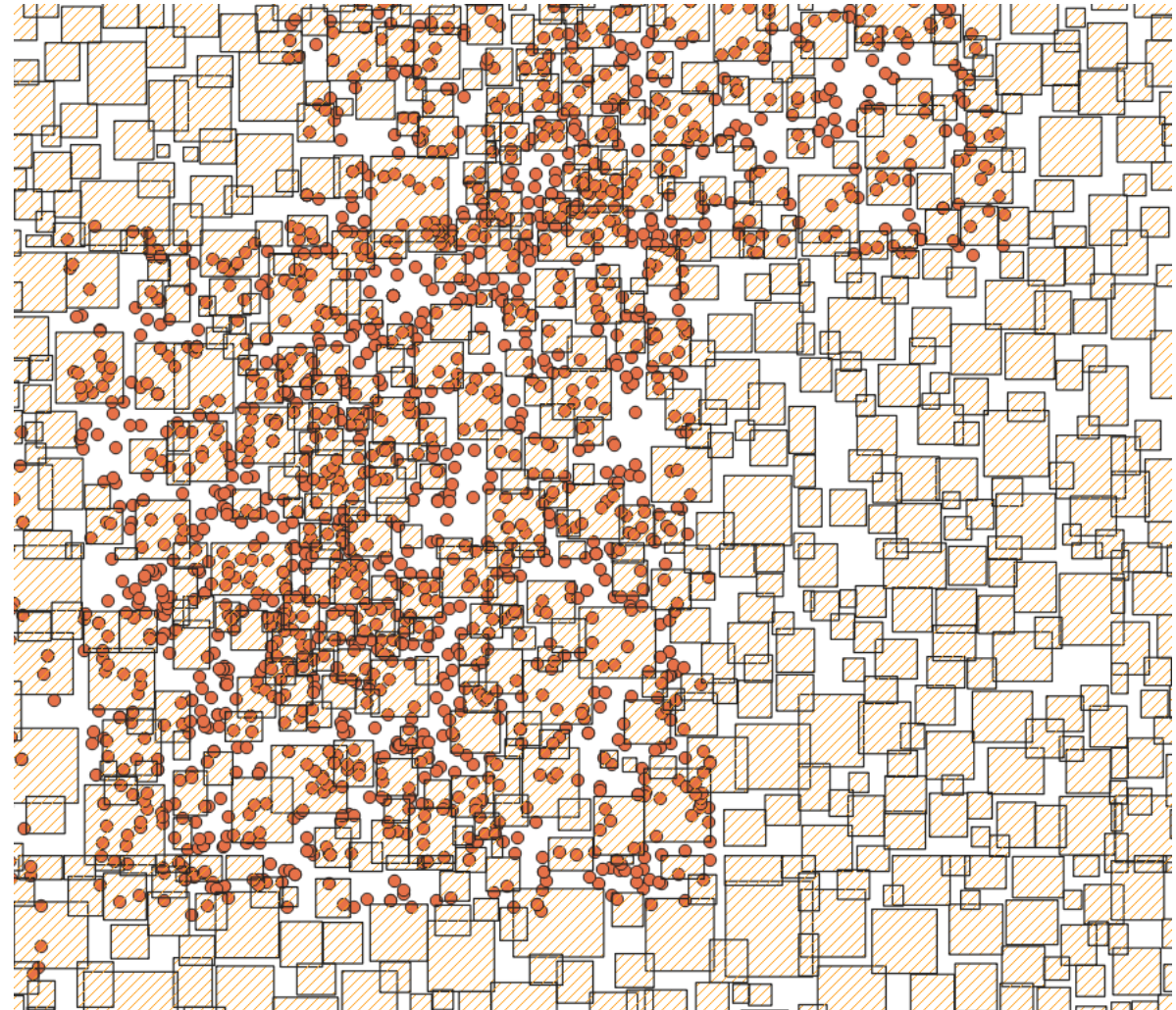
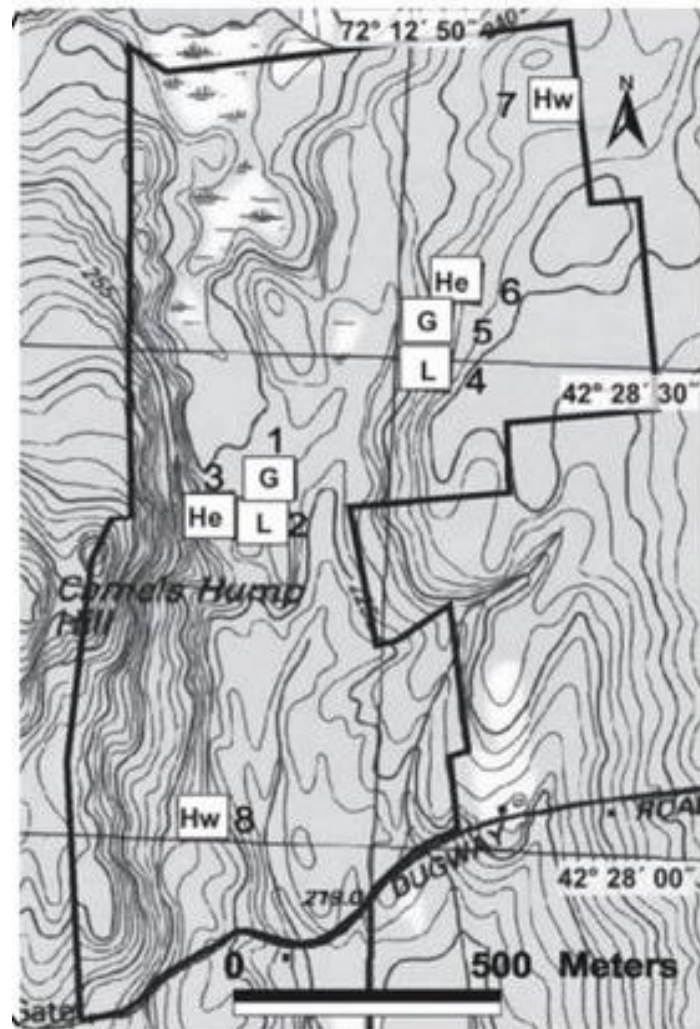
Email: [sydne.record@maine.edu](mailto:sydne.record@maine.edu)

 [@recordlab](https://twitter.com/recordlab)





# NEON remotely sensed crowns & Hemlock Removal Experiment in-situ trees




# Challenges to understanding understory vegetation structure from remotely sensed data

**Global Ecology  
and Biogeography**

A Journal of  
Macroecology

RESEARCH ARTICLE |  Open Access | 

## Towards mapping biodiversity from above: Can fusing lidar and hyperspectral remote sensing predict taxonomic, functional, and phylogenetic tree diversity in temperate forests?

Aaron G. Kamoske , Kyla M. Dahlin, Quentin D. Read, Sydne Record, Scott C. Stark, Shawn P. Serbin, Phoebe L. Zarnetske

First published: 13 May 2022 | <https://doi.org/10.1111/geb.13516>

The core objective of this research is to :  
incorporate disturbance through time and remote sensing  
into a scaling framework of forest structure and functional diversity.

# *Objective 1: Spatio-temporal modeling of forest structure and diversity*

In situ data across time



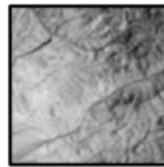
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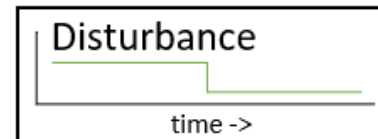
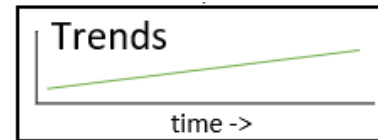
Static & Dynamic RS data



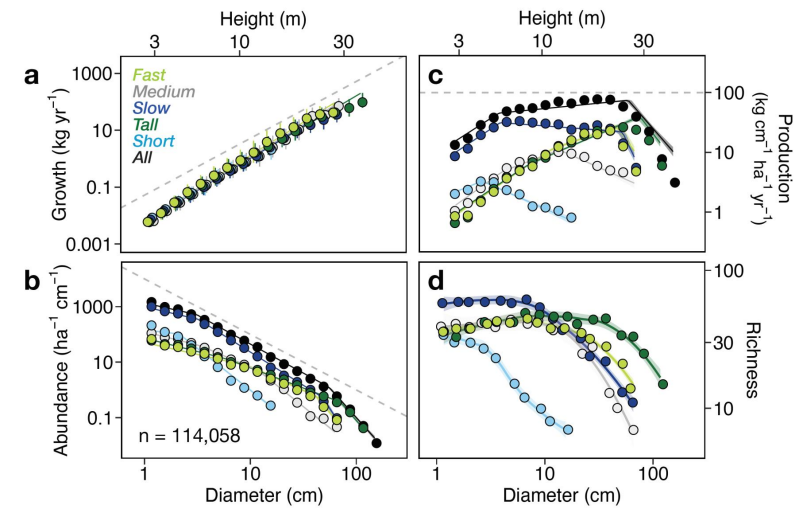
- Elevation
- sd(elev)
- other metrics



- Geologic types
- Shannon entropy
- other metrics

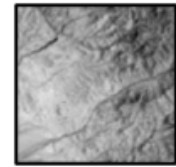
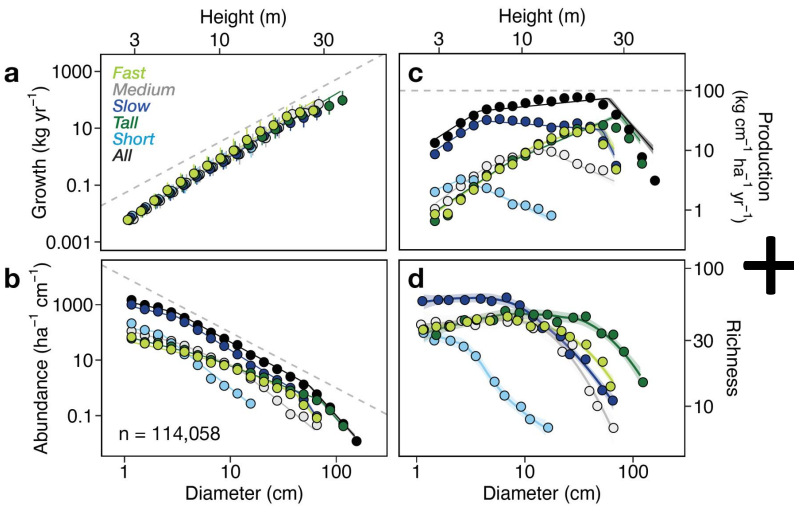


## *Objective 2: Using RS data and models from Obj. 1 to make predictions across space*

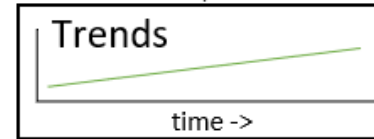


# Objective 2: Using RS data and models from Obj. 1 to make predictions across space

## Static & Dynamic RS data



- Elevation
- sd(elev)
- other metrics



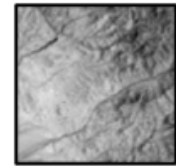
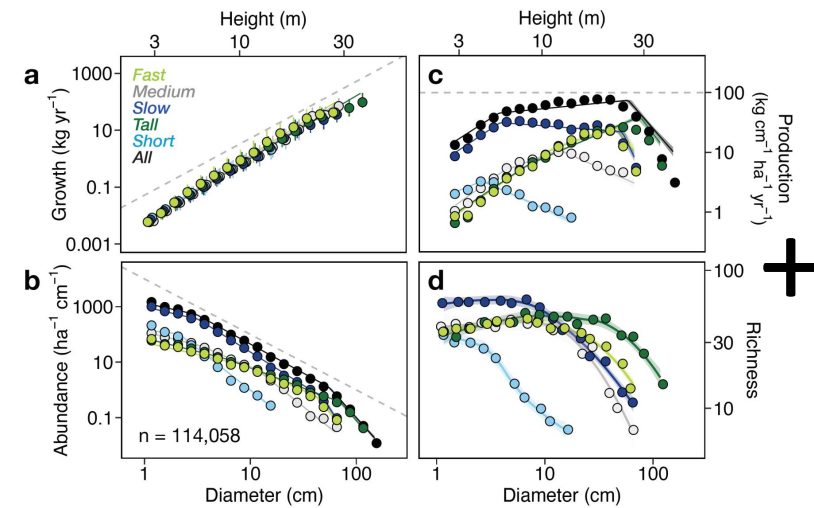
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# Objective 2: Using RS data and models from Obj. 1 to make predictions across space

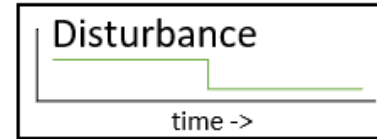
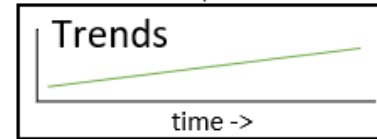
## Static & Dynamic RS data



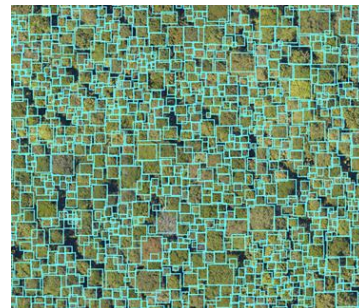
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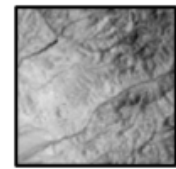
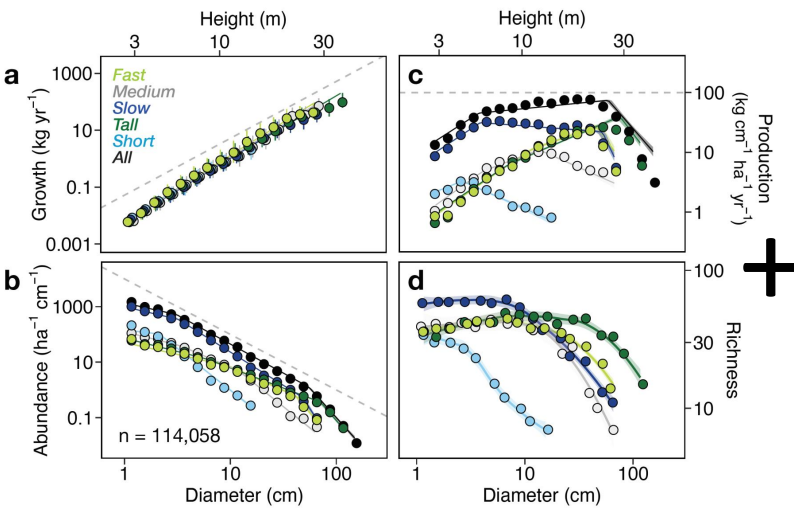


Predictions of functional group abundance and size across space

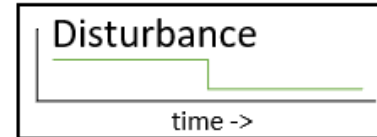
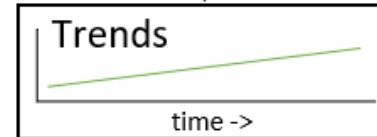


# Objective 2: Using RS data and models from Obj. 1 to make predictions across time

## Static & Dynamic RS data



- Elevation
  - sd(elev)
  - other metrics
- 
- Geologic types
  - Shannon entropy
  - other metrics



Predictions of functional group abundance and size across time



Validation

