Structural Signatures of Moderate Disturbance

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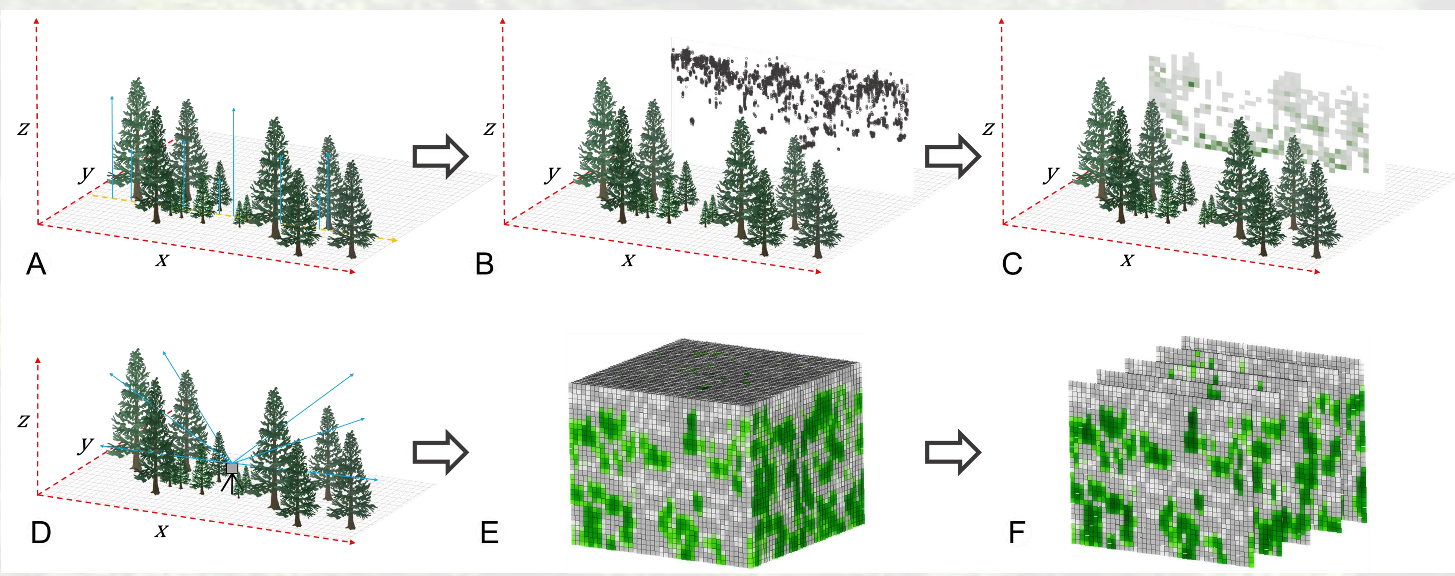
INTRODUCTION

Forests are subject to disturbances from multiple sources, including but not limited to fire, pathogens, insect damage, drought, ice and wind. Classic disturbance ecology focuses on disturbance severity, intensity, and frequency, often with little regard for how different disturbance agents, even at similar levels of severity, may have vastly different structural, and consequently, functional outcomes. Though structural changes could differ significantly at given levels of severity, it follows that functional responses to disturbance may be expected to differ as a result of the acting disturbance agent. Understanding how various disturbance agents reshape forest structure could provide key linkages to understanding structure-function relationships. However, first we must understand how different disturbance agents reshape structure. Machine learning approaches offer solutions to data-rich problems such as this by parsing through complex data sets. Here we use terrestrial LiDAR data coupled with random forest models to test the hypothesis that different types of non-stand replacing, moderate severity disturbance will have unique structural signatures manifest as distinct quantifiable physical changes that can be measured using the canopy structural complexity (CSC) framework.

TERRESTRIAL LIDAR

CSC variables were derived from ground-based, portable canopy LiDAR (PCL) data using the *forestr* package in R. The PCL is an upward facing, near-infrared pulsed-laser operation at 2000 Hz (Riegl LD90 3100 VHS; Riegl USA Inc.) that is user-mounted and generates a continuous x, y vegetation hit grid through a "slice" of canopy via transect sampling.

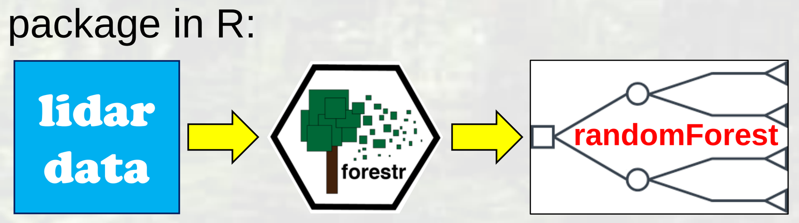
Dr. Hardiman with the PCL at UMBS.



Panels (a–c) show the progression for portable canopy LiDAR (PCL) from data collection (a) through preprocessing (b) to the normalized hit-grid, or matrix of VAI (c) from which higher-order statistics are calculated. Panels (d–f) show progression for terrestrial scanning LiDAR from data collection (d) to voxelization based on the 3-D point cloud (e) to pixelated hit grids of VAI, sliced from the point cloud. From *Atkins et al. 2018 MEE*.

STRUCTURAL SIGNATURE CLASSIFICATION

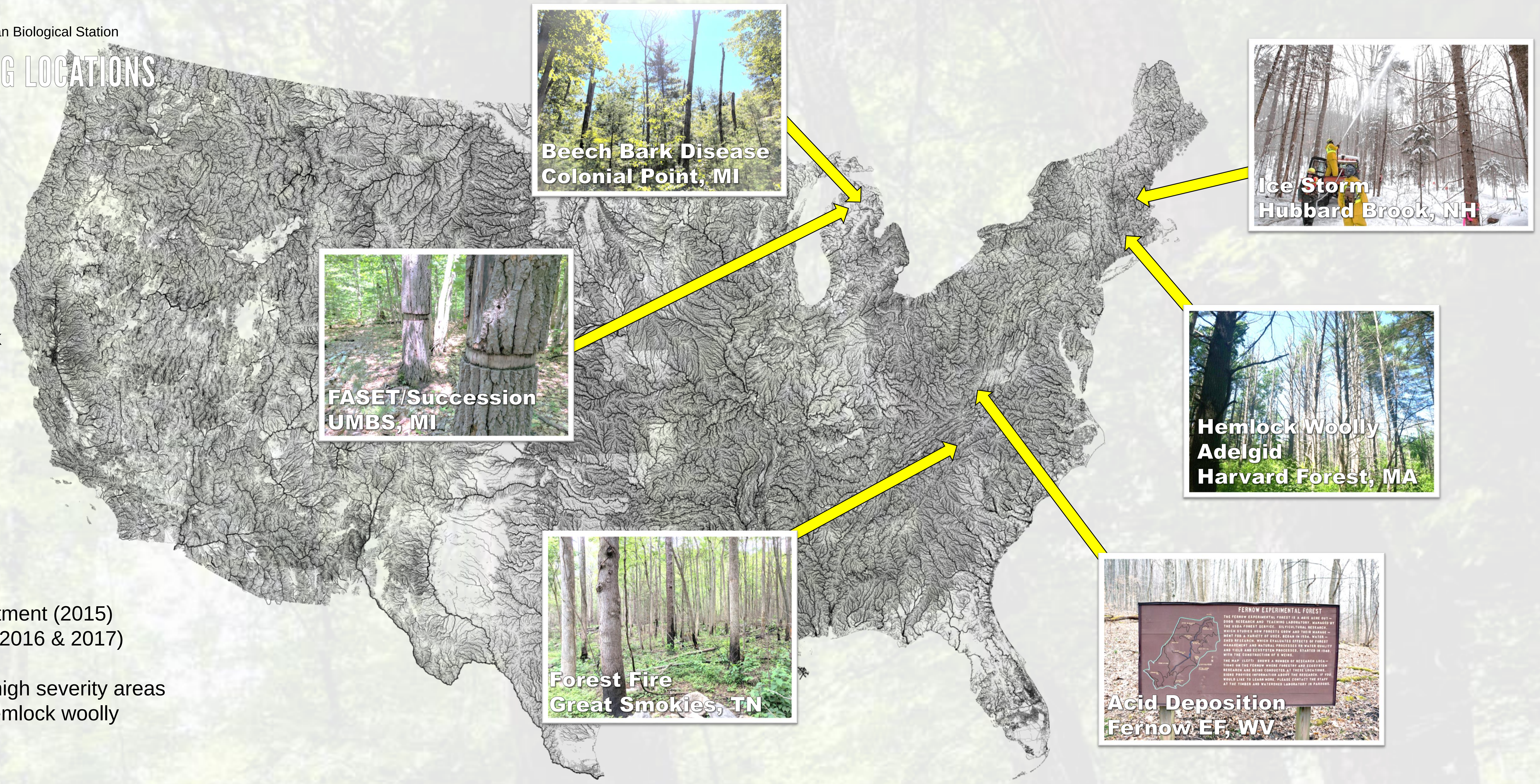
- lidar data processed w/ *forestr in R* (Atkins et al. 2018) to derive CSC metrics
- Classifications made using random forest (RF) models with the randomForest package in R:



  - RF produces a series of iterative decision trees using binary, recursive partitioning that is based on "known classes".
  - Treatment/Control, Pre/Post, or Low/High severity were used as "known classes" in each RF model generated for each disturbance agent.
  - CSC metrics were then fit to classes via RF
- Classification accuracy evaluated as out-of-bag error with the most parsimonious model retained vs. a "kitchen sink" model

FIELD DATA & SAMPLING LOCATIONS

- GRSM – Ground fire. Pre-fire (2016) compared to post-fire (2017)
- Fernow – Treatment watershed (amended w/ $(NH_4)_2SO_4$ annually since 1987) against control
- Colonial Point – Beech bark disease. Pre-disturbance (2012) compared to post-disturbance 2016
- UMBS – Accelerated succession via stem girdling. Treatment forest (FASET) against control forest (UMBS-Ameriflux)
- HBEF – Ice storm. Pre-treatment (2015) against the post-treatment (2016 & 2017)
- Harvard Forest – Low and high severity areas of the forest impacted by hemlock woolly adelgid contrasted (2017)



RESULTS

* Lower classification accuracy indicate more precise model fit based on known classes.

Site	Classification Accuracy (OOB)	Model Constituents
GRSM	22.22% (n = 37)	VAI$_{max}$, VAI, MOCH, VAI$_{peak}$
Fernow	20% (n = 30)	MOCH, P$_C$, σVAI$_{max}$, σH
Colonial Point	9.84% (n = 61)	P$_C$, VAI$_{peak}$, VAI$_{max}$
UMBS (2012)	11.43% (n = 175)	P$_C$, H, MOCH, R$_C$, ENL, σH, Ω
UMBS (2016)	20.97% (n = 62)	R$_C$, MOCH, R$_T$, Ω, P$_C$, H$_{max}$
HBEF (2015-2016)	14.00% (n = 100)	VAI$_{peak}$, R$_C$, MOCH
HBEF (2015-2017)	19.19% (n = 99)	VAI$_{peak}$, R$_C$, ENL, Θ
HBEF (2016-2017)	33.33% (n = 99)	VAI$_{max}$, R$_T$, H$_{max}$
Harvard Forest	5.26% (n = 38)	R$_C$, σVAI$_{max}$, H$_{max}$

Canopy Structural Complexity (CSC) Glossary

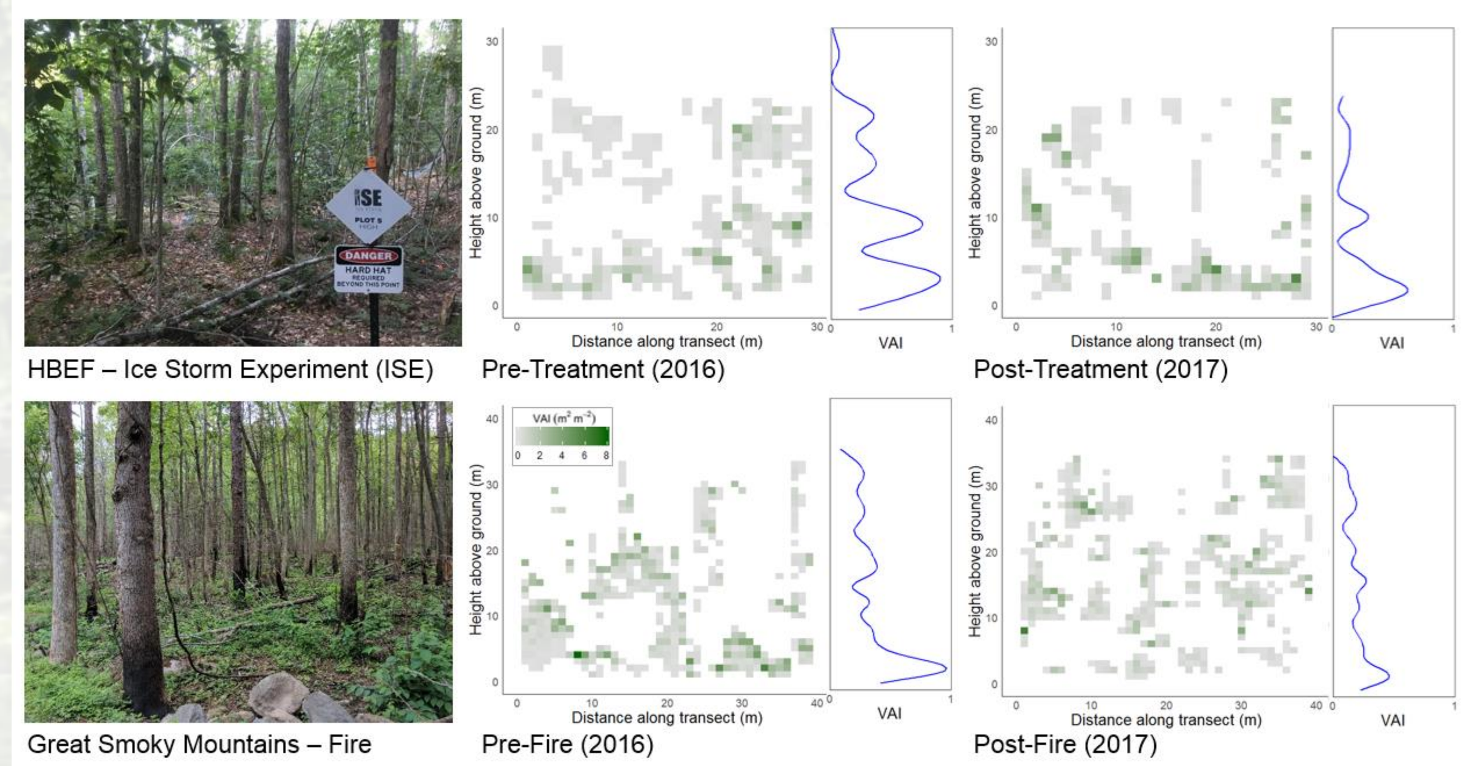
VAI – vegetation area index ($m^2\ m^{-2}$)
VAI$_{max}$ – max *x, z* value of vegetation area index ($m^2\ m^{-2}$)
VAI$_{peak}$ - transect/plot mean of VAI$_{max}$ ($m^2\ m^{-2}$)
σVAI$_{max}$ – standard deviation of VAI$_{max}$ ($m^2\ m^{-2}$)
H – mean leaf height (m)
σH – standard deviation of mean leaf height (m)
MOCH – mean outer canopy height (m)

P$_C$ – canopy porosity, ratio of void to filled space in the canopy
R$_C$ – canopy rugosity (m), accumulated *x* and *z* variance
R$_T$ – top rugosity (m), standard deviation of final returns
ENL – effective number of layers, a measure of occupation of 1 m wide layers by vegetation relative to total space
Θ - gap fraction, ratio of sky to canopy returns of outer surface
Ω – clumping index, degree of foliar clumping

CONCLUSIONS

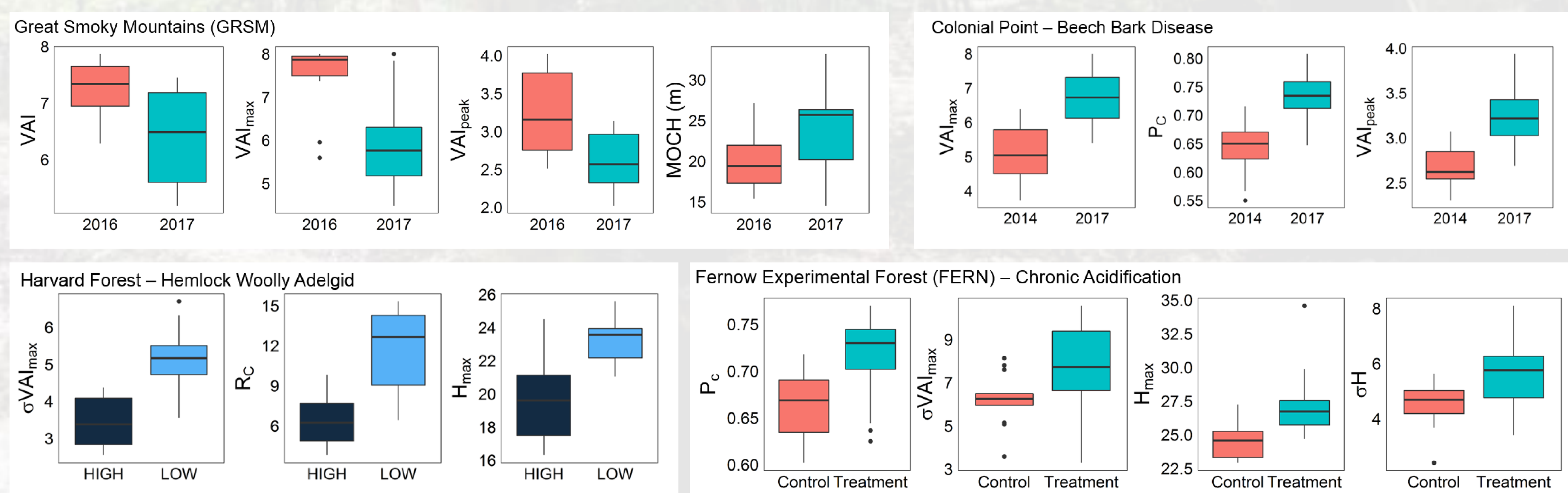
- CSC offers potential to structurally classify disturbances
- Functional/structural linkages could inform ecological impacts of disturbance
- Potential for scaling and modeling as CSC begins to be incorporated more fully into ecosystem models
- Move beyond biomass/leaf-area only descriptors of disturbance to more fully characterize change

VEGETATION SHIFTS



At top, Hubbard Brook Experimental Forest Ice Storm Experiment (ISE). Post-treatment, the VAI distribution shifts downward as upper canopy is lost. At bottom, Great Smoky Mountains where the fire results in a loss of VAI density at lower canopy positions.

Below, boxplots showing differences among classes of significant model constituents for Great Smoky Mountains, Colonial Point, Harvard Forest, and Fernow Experimental Forest.



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