

Quantitative Community Ecology in an Era of Global Change: Integrating Empirical Research, Model Development, and Data Synthesis

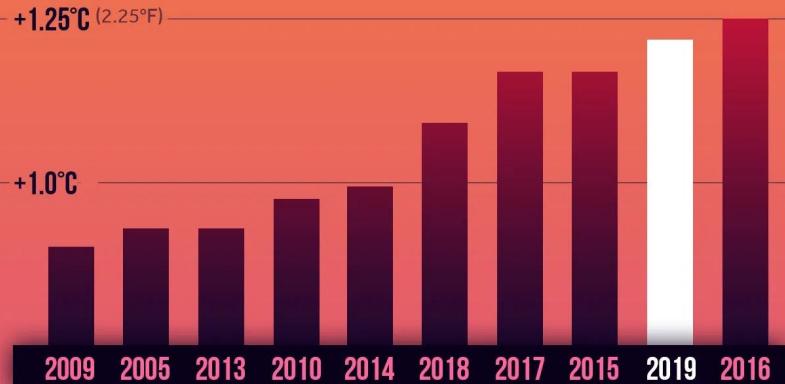
Daijiang Li

@_djli <https://daijiang.name>

University of Florida

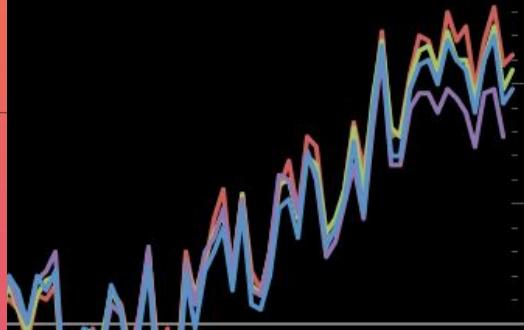
10 HOTTEST YEARS ON RECORD GLOBALLY

Last 5 = Hottest 5



Source: NASA GISS & NCDC
and adjusted to early 2019

sts can't
ture changes.

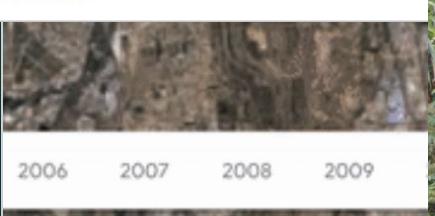


Global Changes

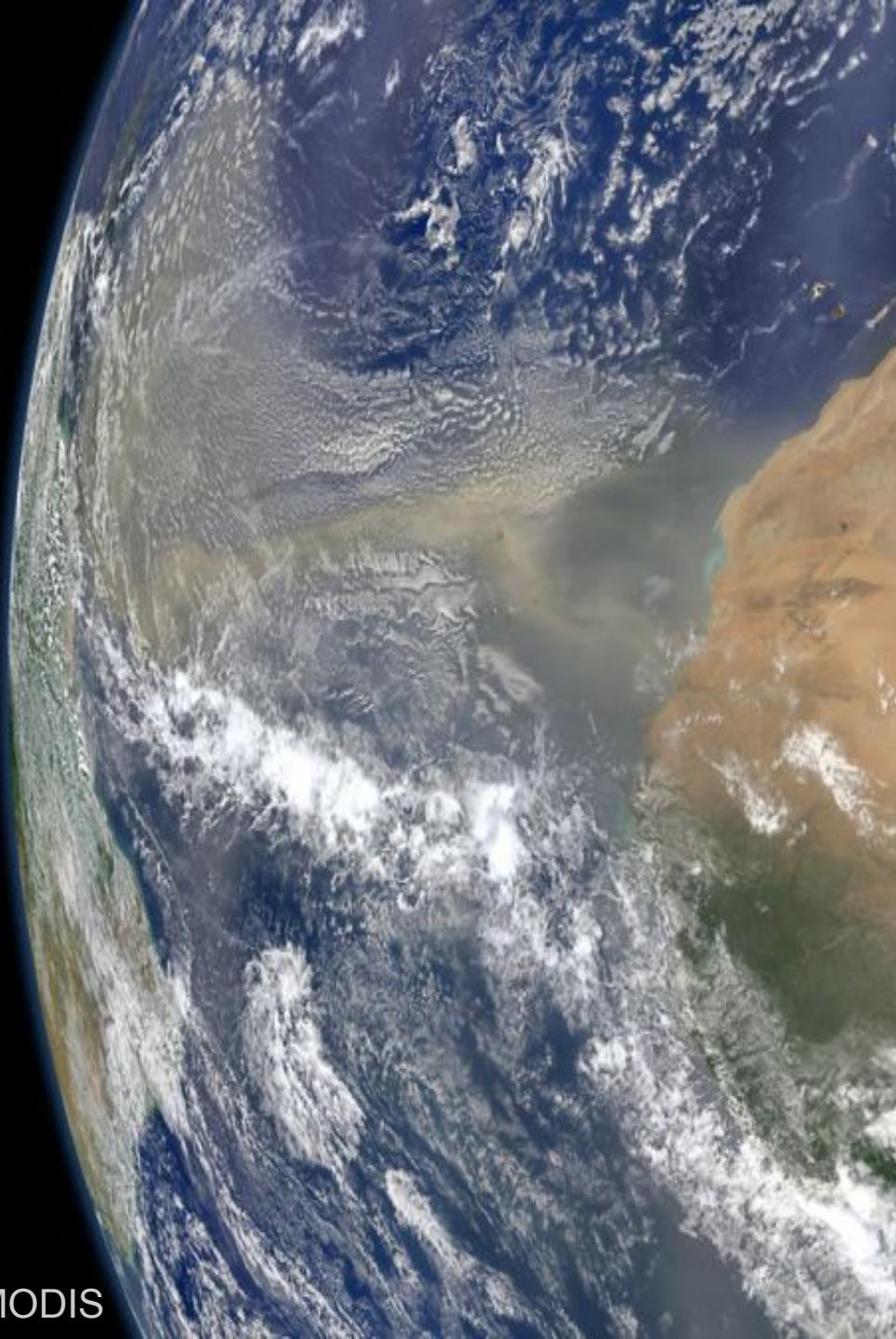
2019 Was the Second Hottest Year on Record

Second Hottest Year on Record

By Eric Roston, January 15, 2020



How have
global changes
interactively
affected plant
communities?



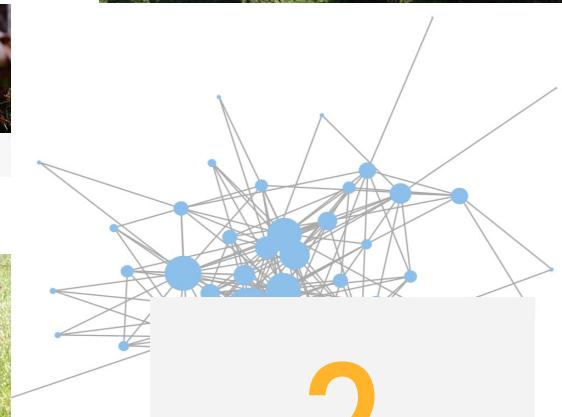
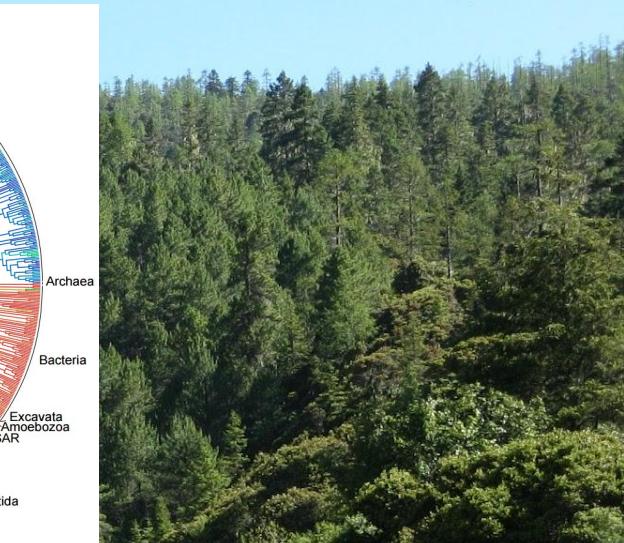
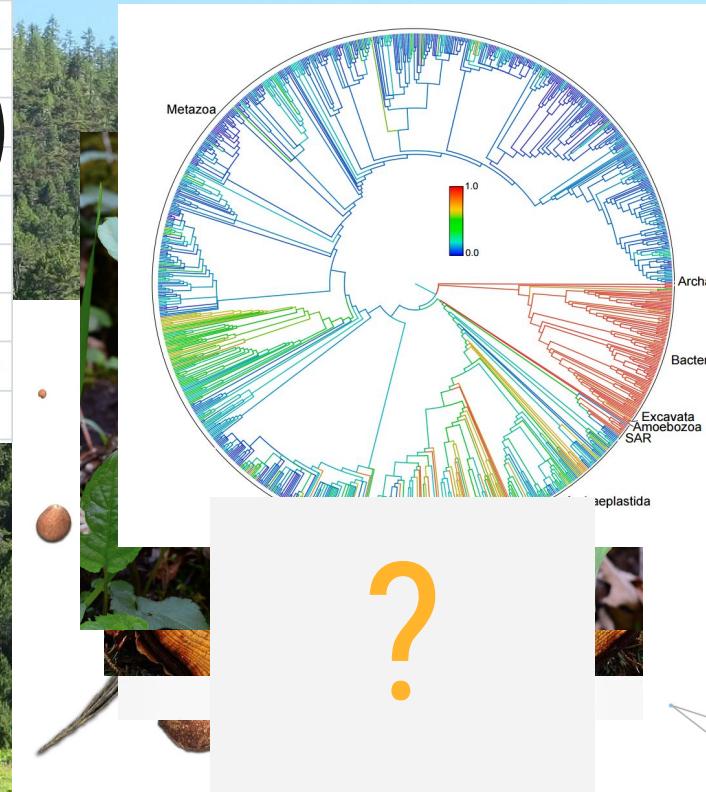
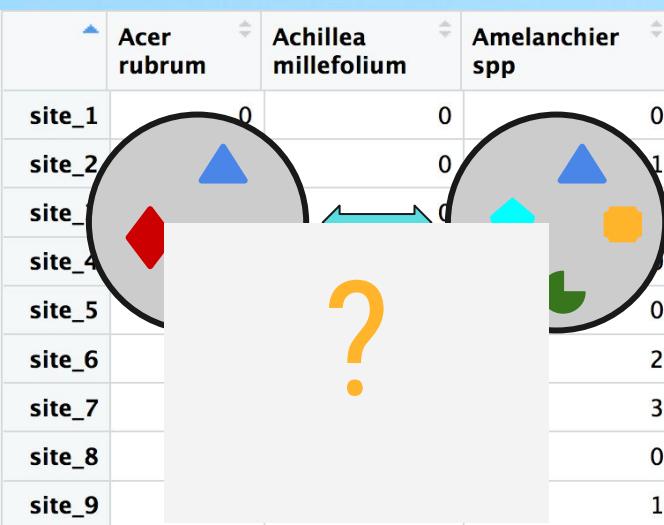
Research projects

1. Field research on plant community changes at the regional scale
2. Development of novel statistical models to get more out of field data
3. Analysis of big data to study global changes at the continental scale

Why should we care about plant communities?



Ways to measure a plant community?



Research projects

1. Field research on plant community changes at the regional scale
2. Development of novel statistical models to get more out of field data
3. Analysis of big data to study global changes at the continental scale

What do we need?

- A system that has experienced global changes
- Baseline data

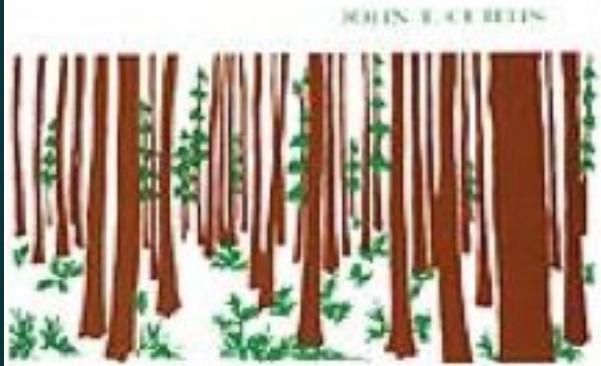


Courtesy of Hugh Iltis

John
Curtis
(1913-1961)



University of Wisconsin
Plant Ecology Laboratory



THE
Vegetation
OF
Wisconsin

AN ORDINATION OF PLANT COMMUNITIES



Jack pine
(*Pinus banksiana*)



Northern pin oak
(*Quercus ellipsoidalis*)

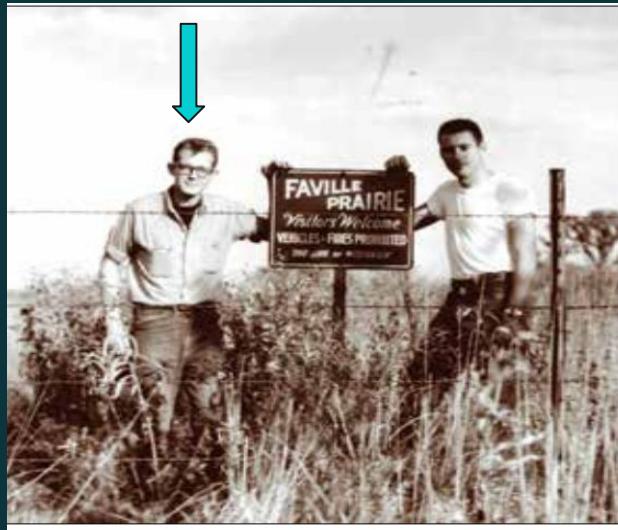
James R. Habeck (1958)

Wisconsin Academy of Science, Arts and Letters

A PHYTOSOCIOLOGICAL STUDY OF THE UPLAND FOREST COMMUNITIES IN THE CENTRAL WISCONSIN SAND PLAIN AREA¹

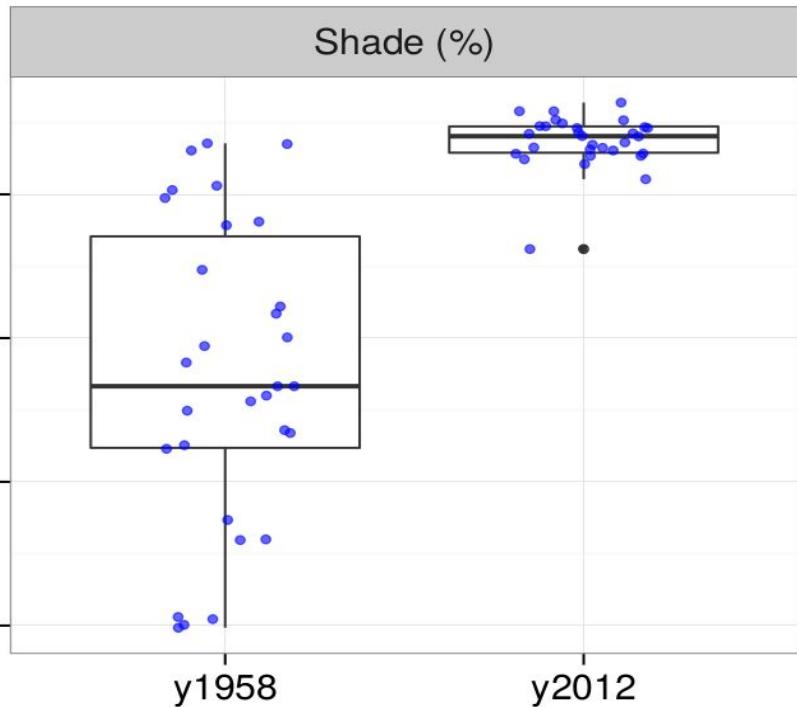
JAMES R. HABECK

Botany Department, University of Wisconsin, Madison



Jim Habeck (left) in the spring of 1955.





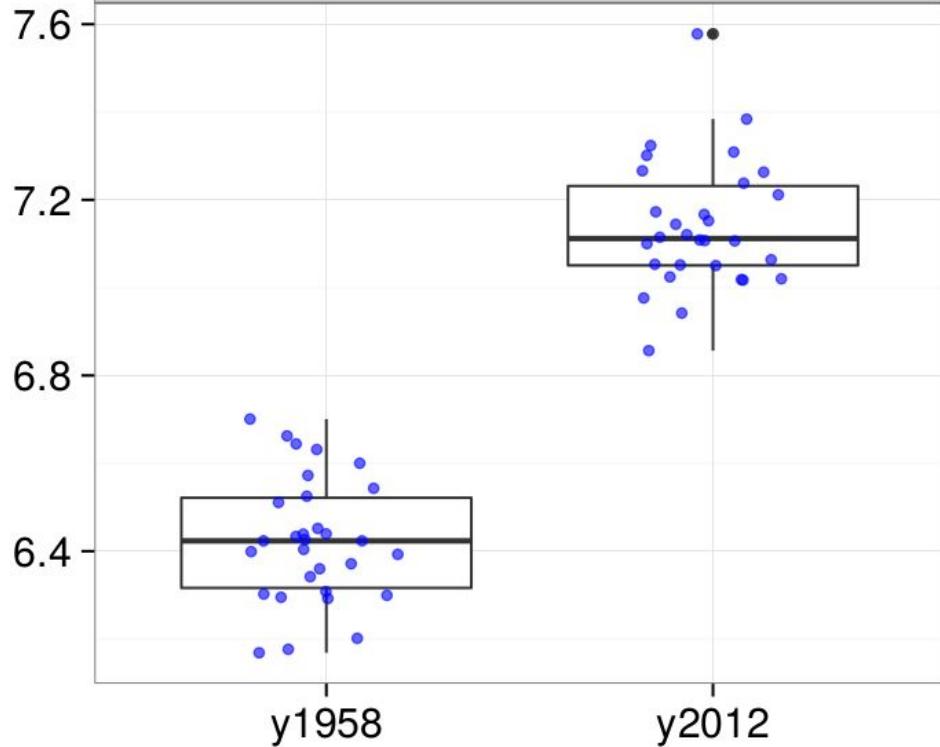
Legend

- Central Sand Plains
- Tension Zone

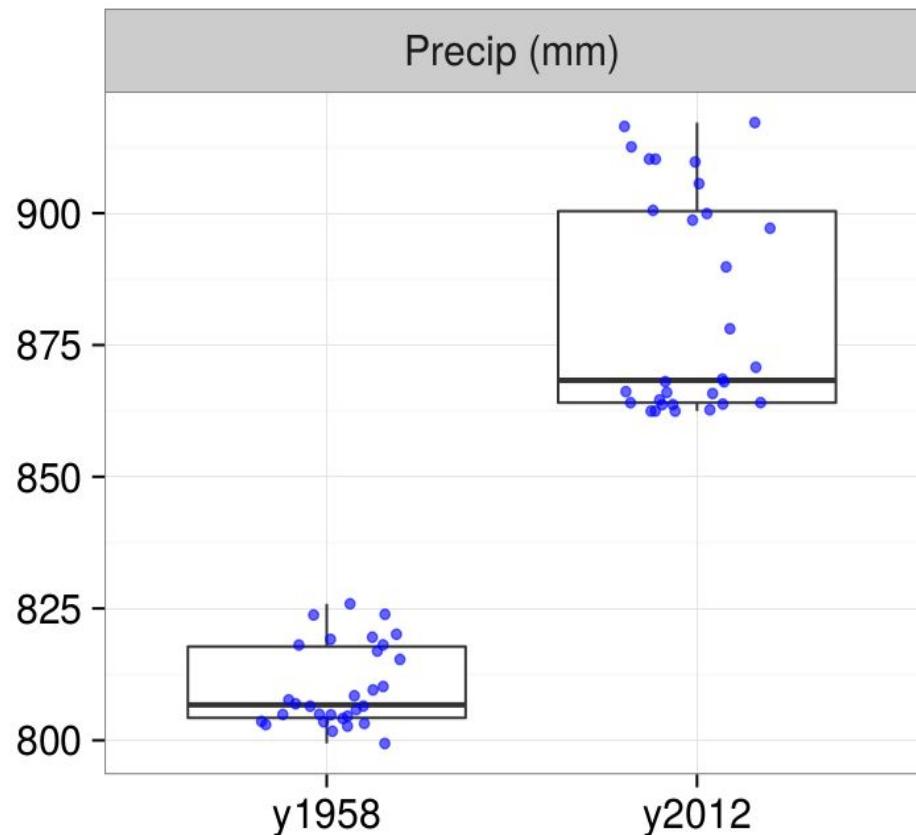


Li & Waller, 2015, *Ecology*

Temp (Celsius degree)



Precip (mm)



How have fire suppression and
climate change affected pine barrens?

Undergrad, UW-Madison
Marian Lea



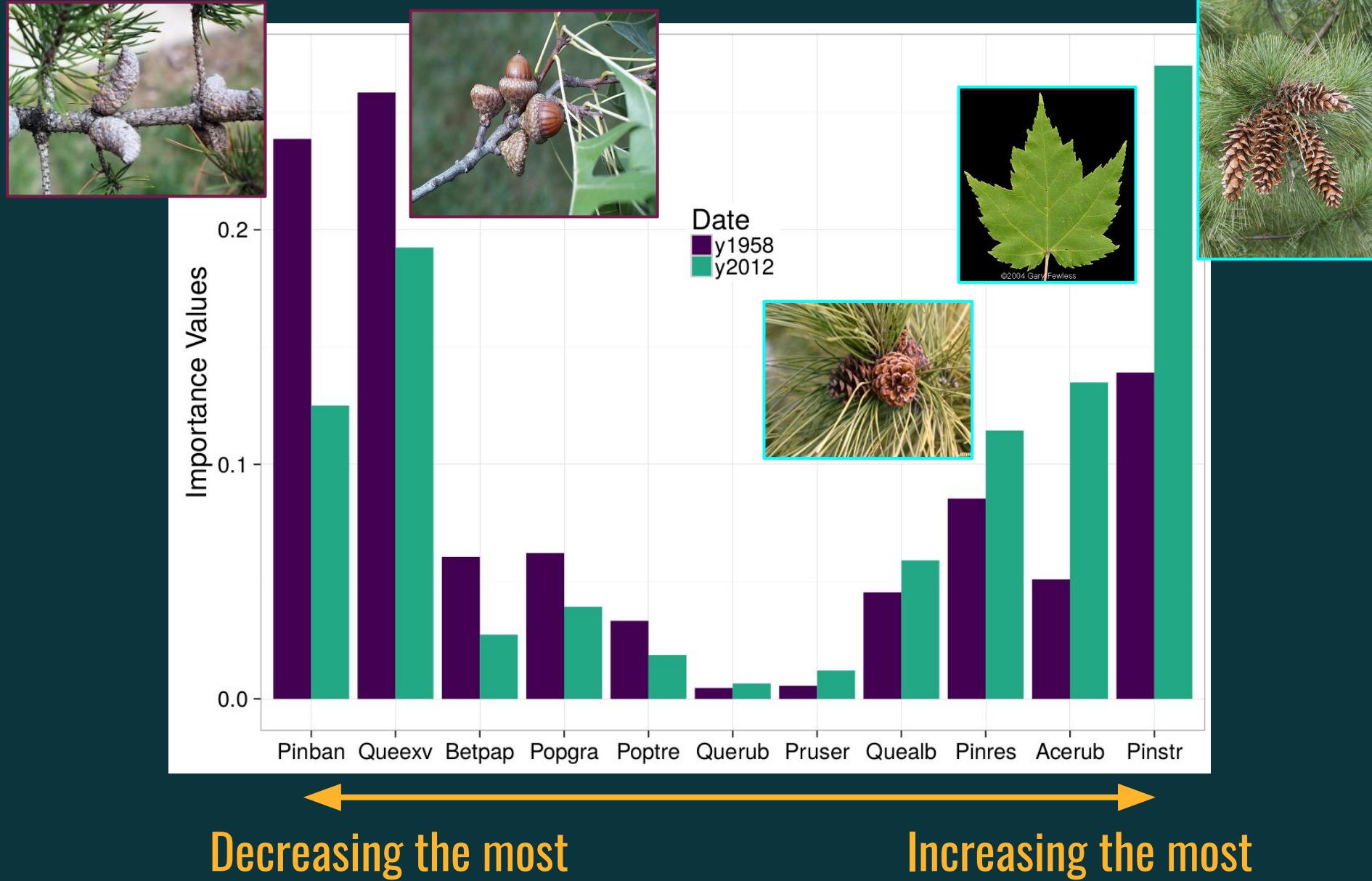
Undergrad, UW-Madison
Amelia Krug



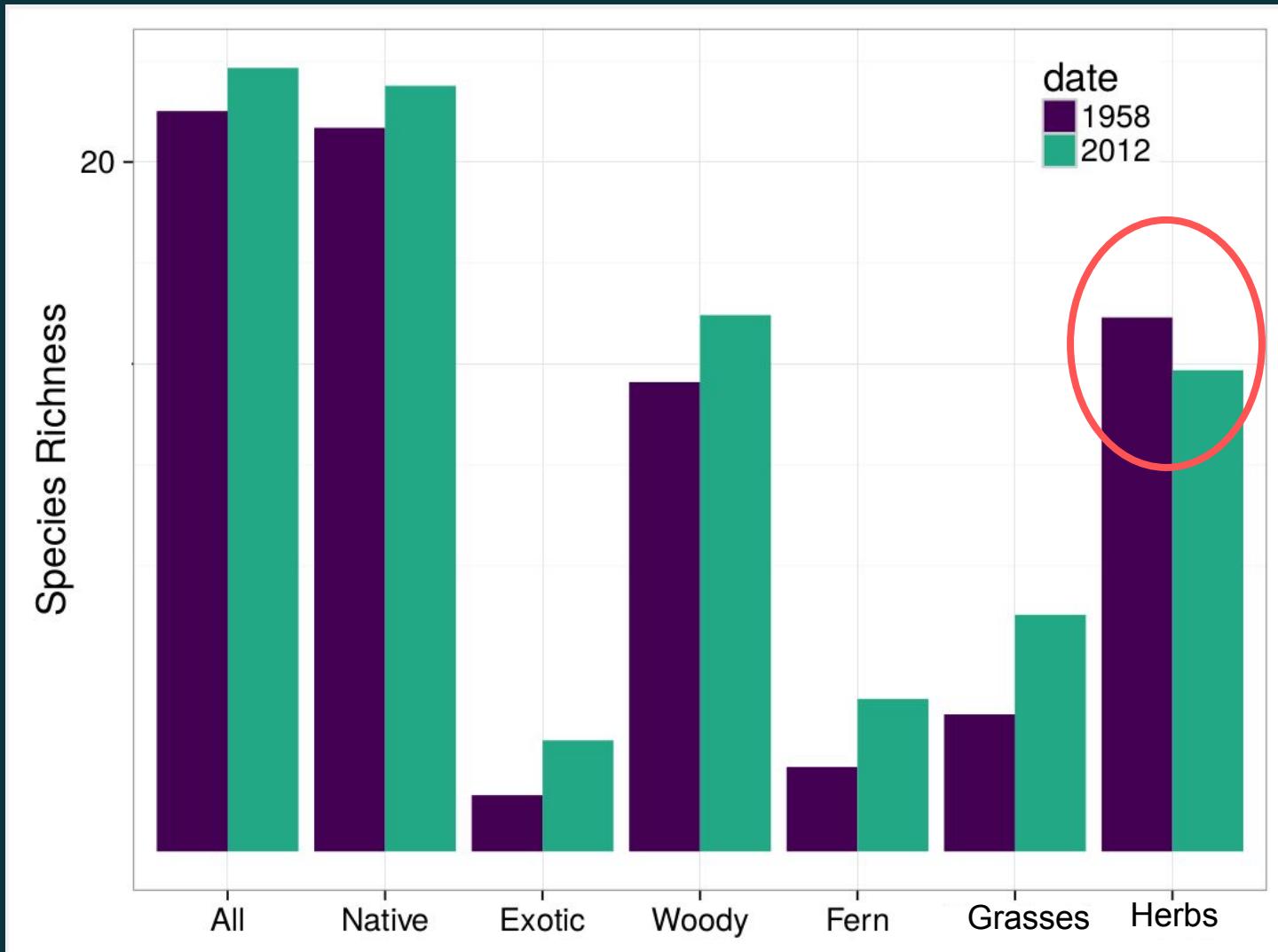
A photograph of a forest scene. In the foreground, there is a fallen log on the ground. The ground is covered with green vegetation and fallen pine needles. In the background, there are many tall evergreen trees, primarily pine and spruce. Some of the trees have fallen or are leaning over. The lighting suggests it is daytime.

08/13/2012 16:00

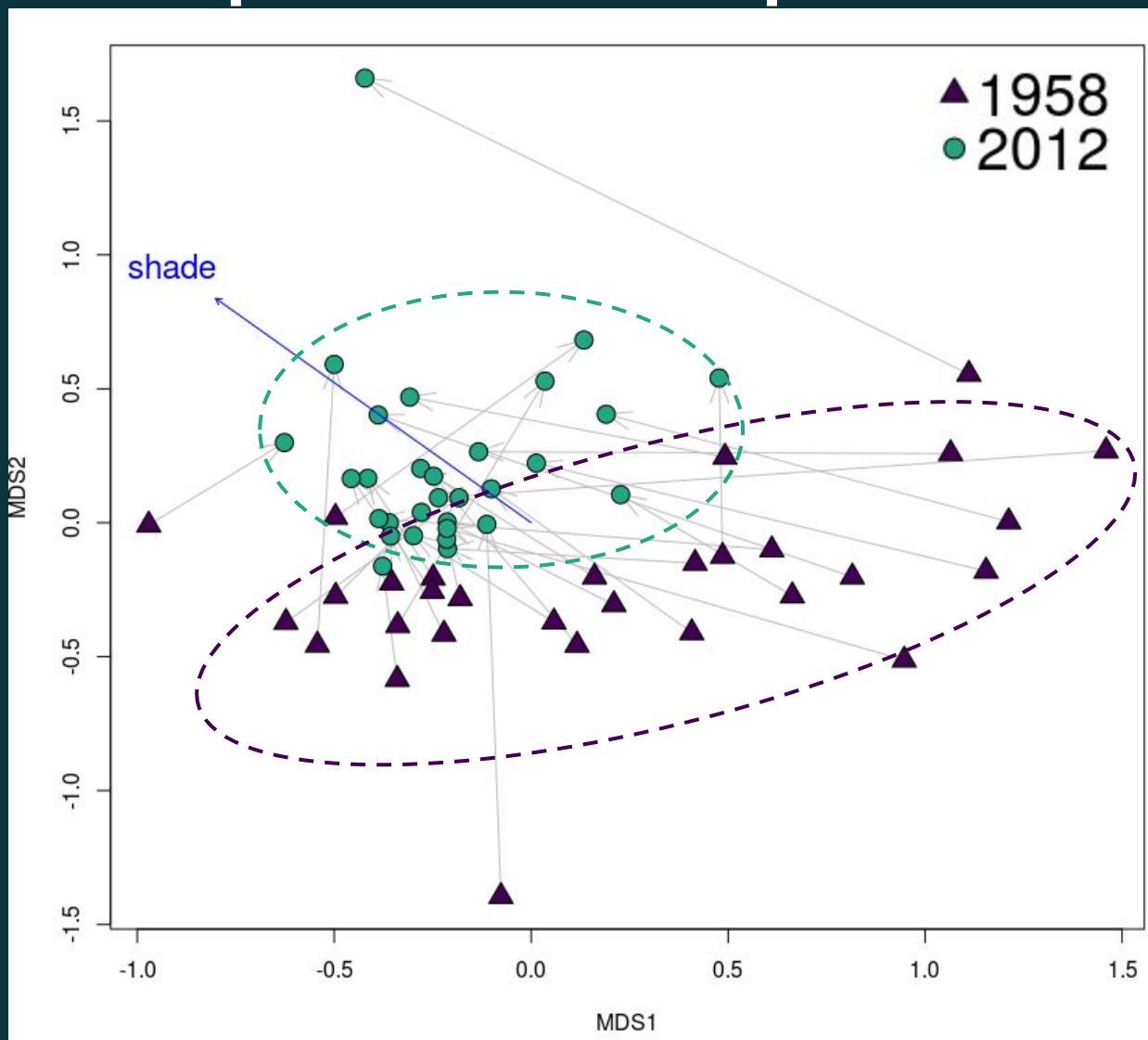
Changes in tree importance values



Changes in understory species diversity

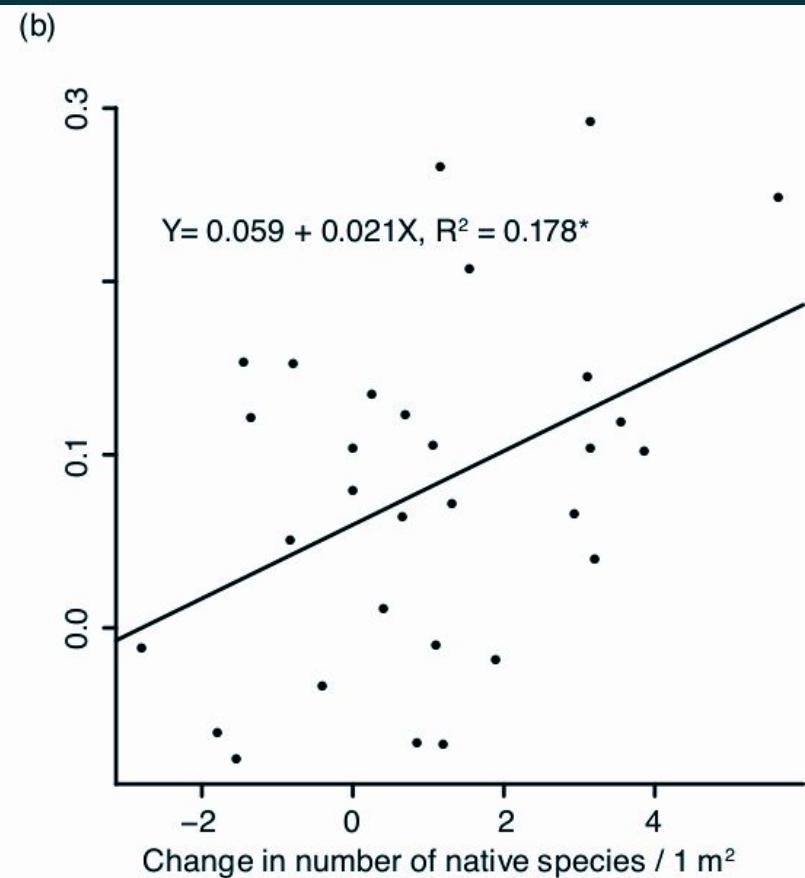
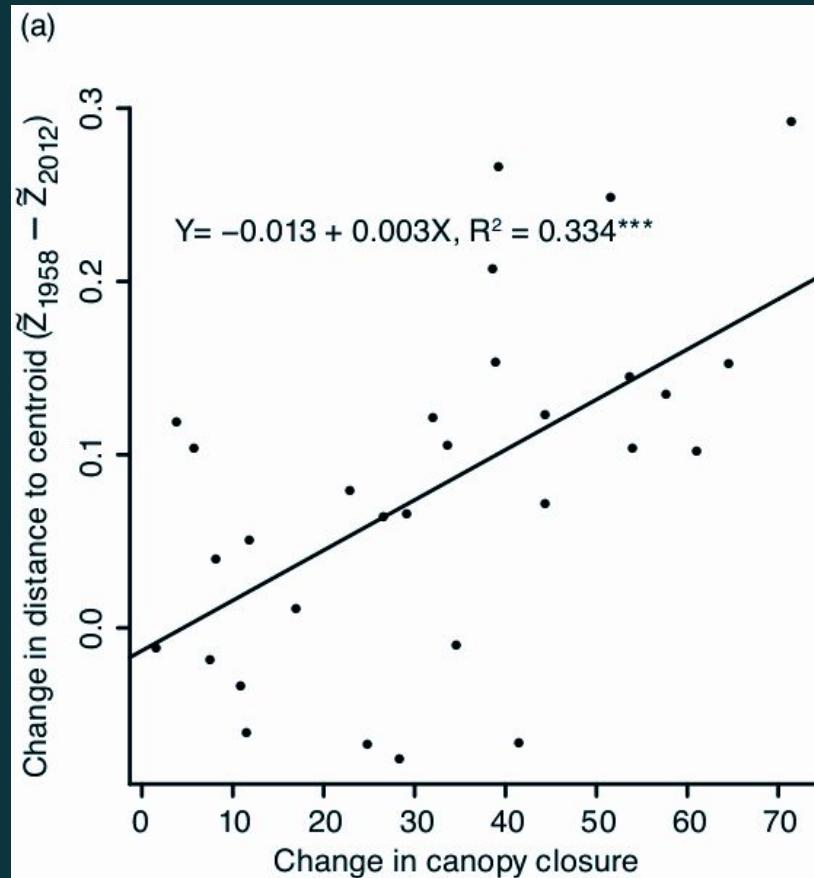


Changes in understory species composition



Drivers of homogenization

High Homogenization



Increasing canopy cover

No climatic variable is significant; no interactions

Increasing native species

Functional traits

Woody

Biotic Pollination

Shade Tolerance

Plant Height

Seed Mass

Specific Leaf Area (SLA, leaf area/dry mass)

Leaf Carbon Content (LCC)

Leaf Nitrogen Content (LNC)

Stem Dry Mass Content (SDMC)

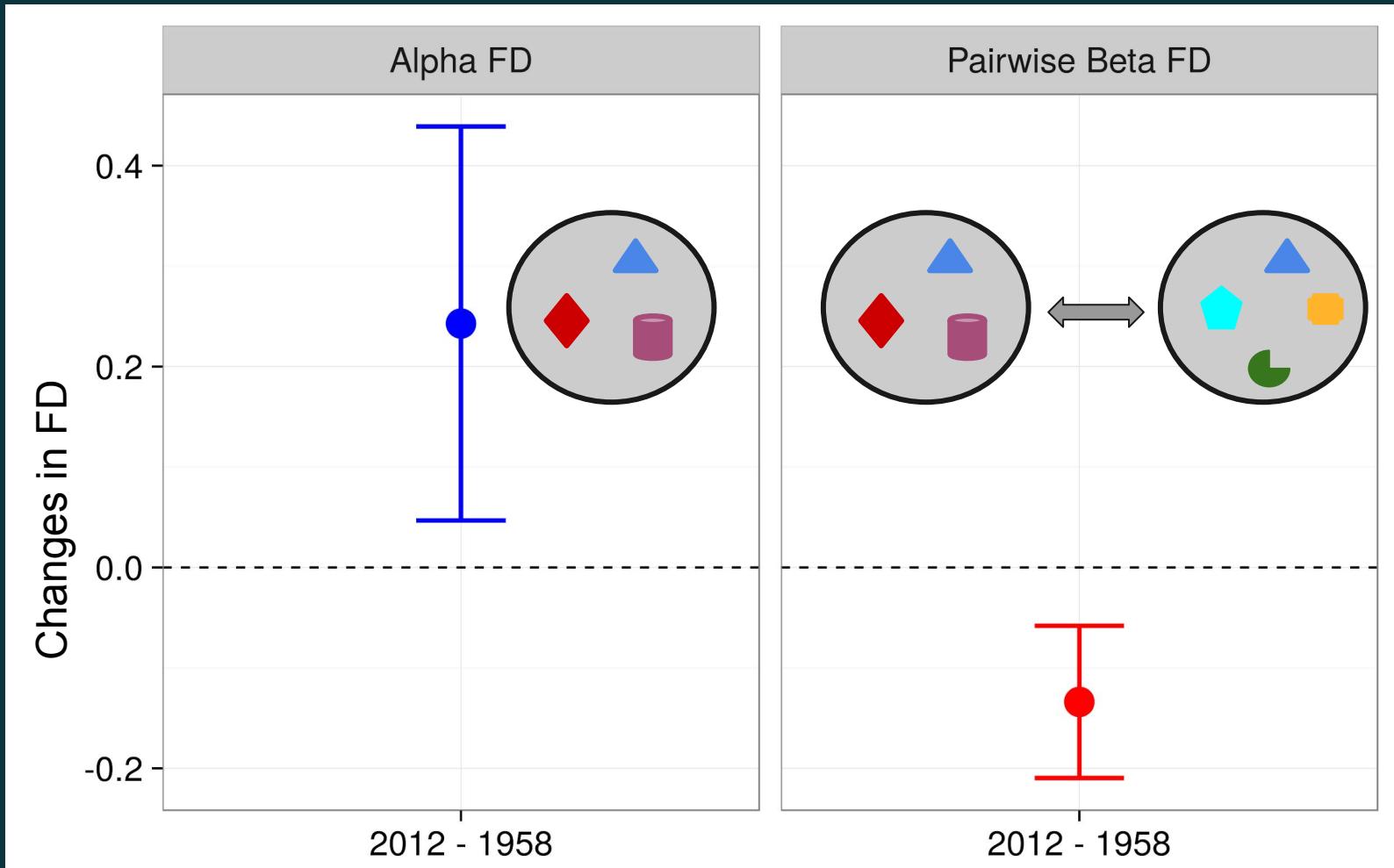
>100 species, including Poison Ivy

Undergraduate students at
UW-Madison:

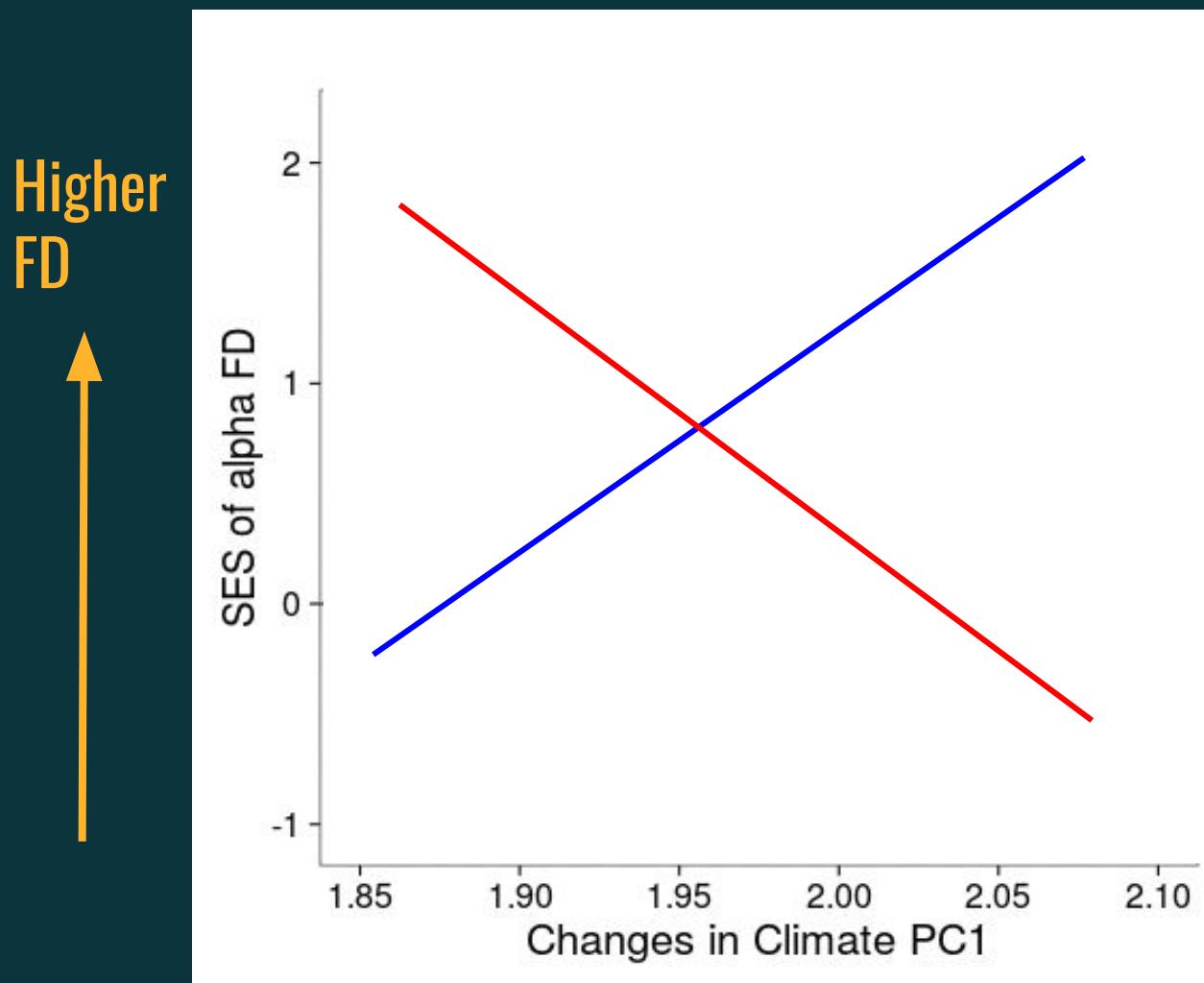
- Alex Arena
- Madeline Grupper
- David Barfknecht
- Kelly Wallin



Functional diversity (FD)



α FD ~ shade:climate



Warmer and Wetter

Species relationships

	A	B	C	D
site_1	1	0	0	0
site_2	0	1	0	0
site_3	1	1	0	1
site_4	0	0	1	0
site_5	1	0	0	1
site_6	1	0	0	0
site_7	1	0	0	0
site_8	0	1	1	1
site_9	0	1	1	0



	A-B	A-C	B-C	B-D
site_1	0	1	0	0
site_2	0	0	0	1
site_3	1	1	1	0
site_4	0	0	0	1
site_5				
site_6				
site_7				
site_8	1	0	1	0
site_9	1	1	0	0



Species composition



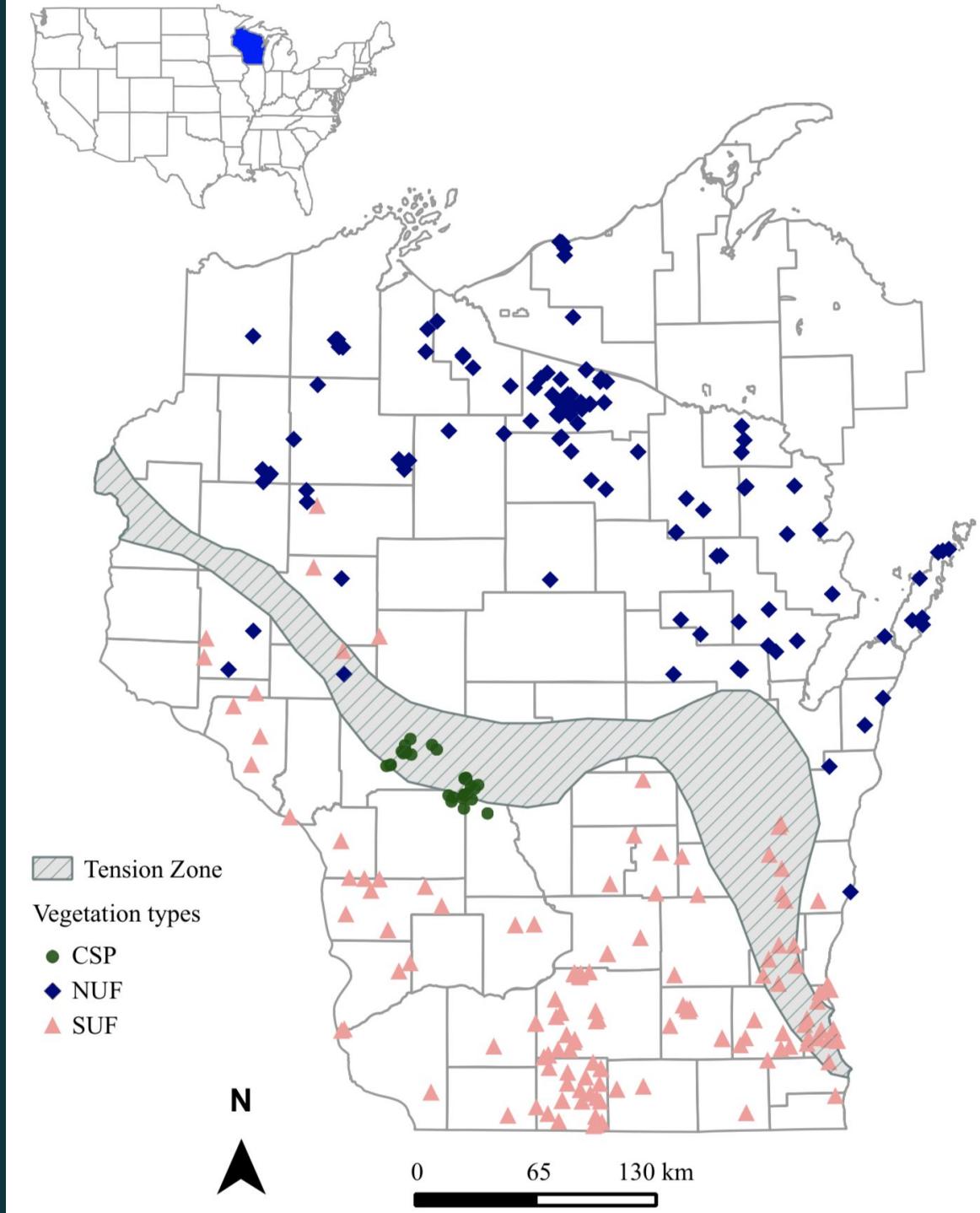
Species association

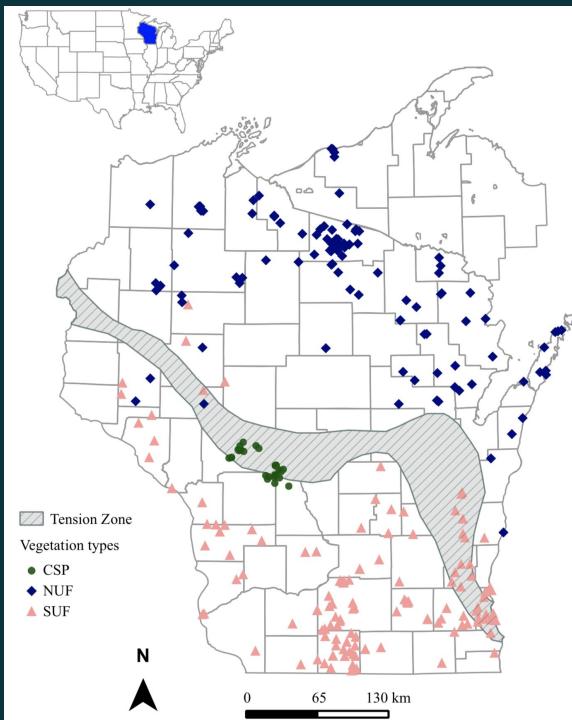


Does homogenization in species composition lead to homogenization in species associations?

266 sites

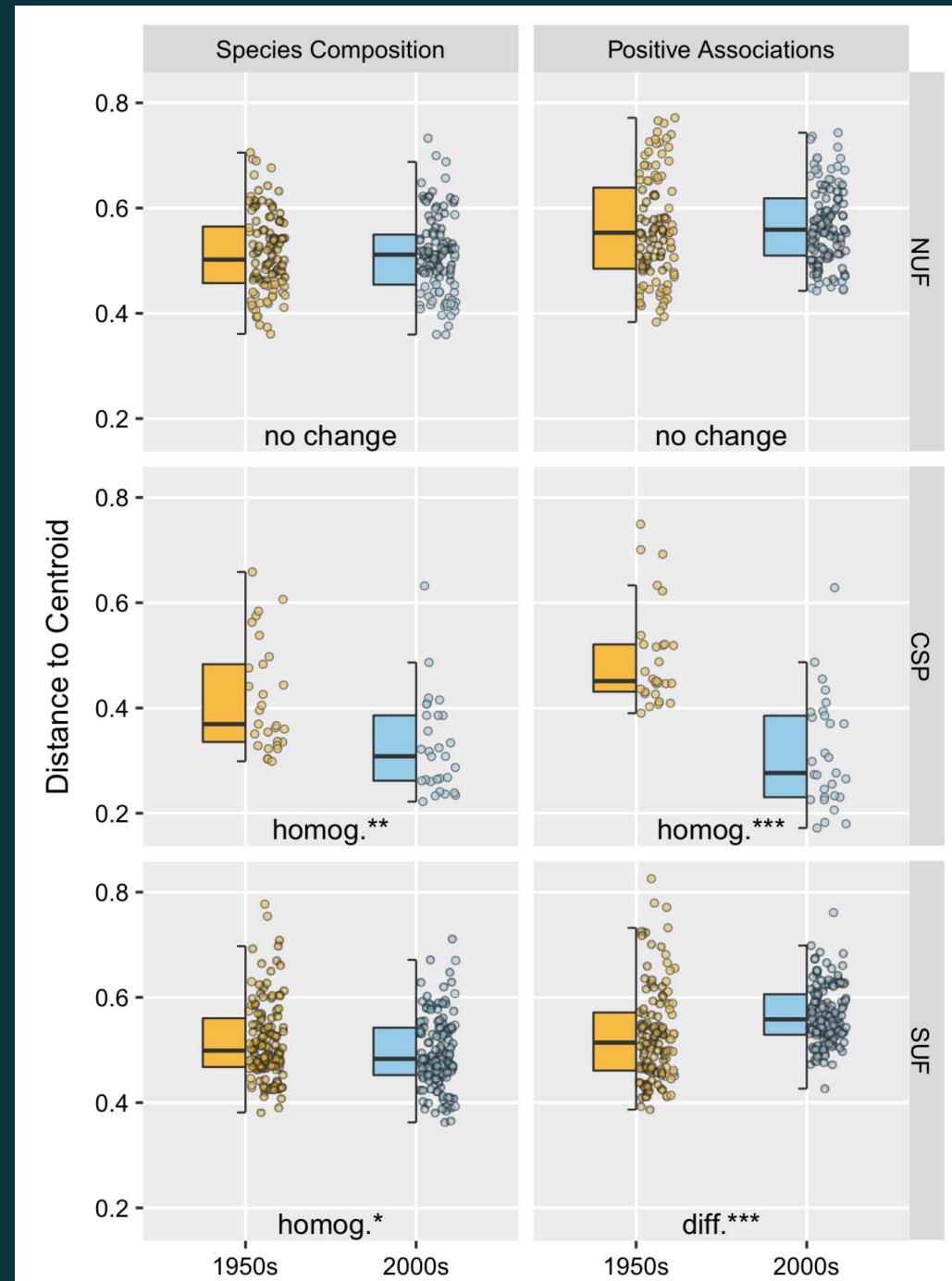
Li & Waller, 2016,
Global Ecology and Biogeography





Decoupled!

Li et al., 2018,
*Global Ecology and
 Biogeography*



Summary

- Increasing local species and functional diversity
- Decreasing regional species and functional diversity (biotic homogenization)
- Long-term dynamics of species composition and association are decoupled

With continuous fire suppression and climate change, future diversity may decrease; novel interactions may be more common

Conservation implications

Research projects

1. Field research on plant community changes at the regional scale
2. Development of novel statistical models to get more out of field data
3. Analysis of big data to study global changes at the continental scale

Example of traditional community analysis

Species composition

	Acer rubrum	Achillea millefolium	Amelanchier spp	Andropogon gerardii
site_1	0	0	0	0
site_2	3	0	1	0
site_3	8	0	0	0
site_4	0	1	0	5
site_5	0	1	0	0
site_6	15	0	2	0
site_7	14	0	3	0
site_8	0	0	0	0
site_9	2	0	1	0

Environmental variables for each site (e.g. soil pH, climate, etc.)

m sites

Diversity (per site)

Multivariate analysis (e.g. ordination)

n species

Functional traits for each species (e.g. height, leaf C %, etc.)

Algorithmic!

Example of model-based community analysis

$$\log(Y_i + 1) = \alpha + a_{\text{spp}[i]} + b_{\text{site}[i]} + (\beta_1 + c_{\text{spp}[i]}) \text{env1}_{\text{site}[i]} + \beta_2 \text{trait1}_{\text{spp}[i]} + \beta_3 \text{env1}_{\text{site}[i]} \times \text{trait1}_{\text{spp}[i]} + e_i$$

Abundance of species among sites

Species as random effect

Site as random effect

Average effect of env1

Effects of env1 to sp as random effect

Overall species abund.

Average effect of trait1

Interaction between env1 and trait1

$i: 1, 2, \dots, nm$

α, β : fixed terms

a, b, c : random terms

e : error term

$a \sim \text{Gaussian}(\mathbf{0}, \sigma_a^2 \mathbf{I}_n)$

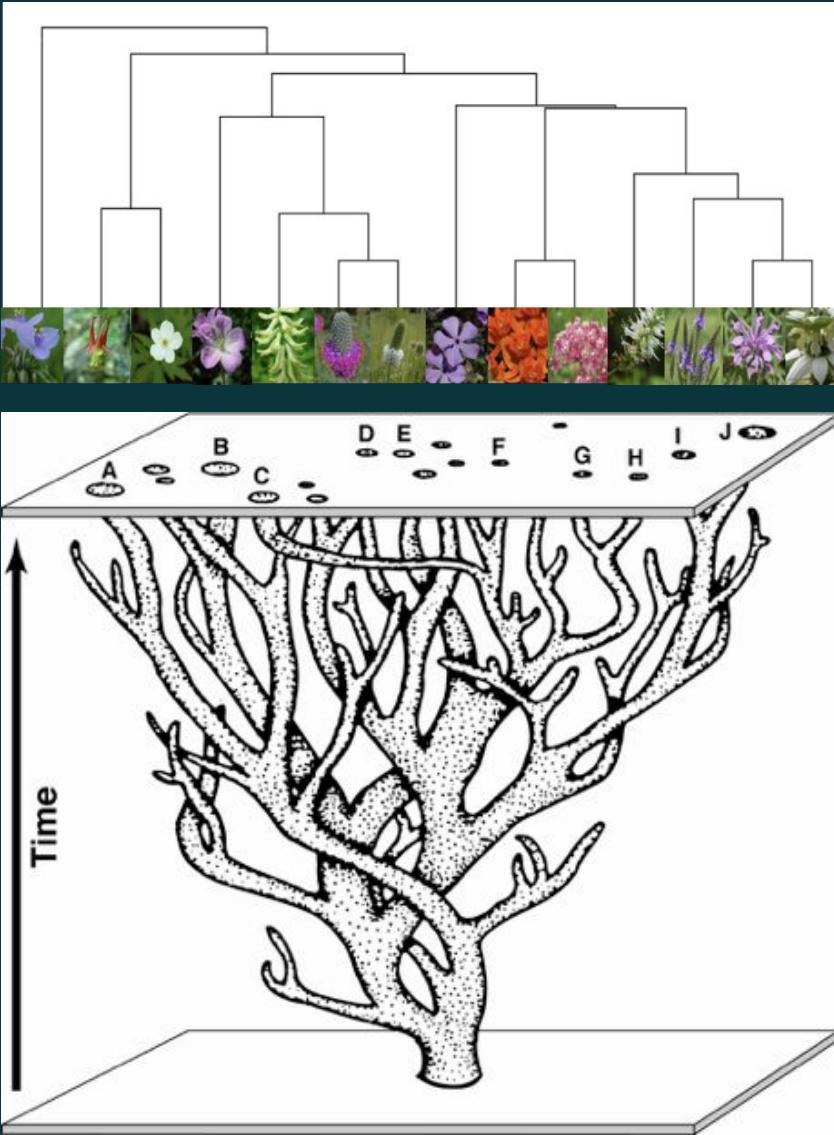
$b \sim \text{Gaussian}(\mathbf{0}, \sigma_b^2 \mathbf{I}_m)$

$c \sim \text{Gaussian}(\mathbf{0}, \sigma_c^2 \mathbf{I}_n)$

$e \sim \text{Gaussian}(\mathbf{0}, \sigma_e^2 \mathbf{I}_{mn})$

Why model-based methods?

- No aggregation to one value/site
- Integrate multiple source of information (and their interactions)
- Model validation/selection/prediction ...
- Deeper understanding of community dynamics



Problem

Species are
not independent
samples from the
same statistical
distribution

- Inflated type I error (false positive)
- Well-known problem from comparative analyses
(Felsenstein 1985; Harvey & Pagel 1991; Garland et al. 1999; Paradis 2012;
Garamszegi 2014)
- Same problem for community analyses?

Model-based community analysis

Phylogenetic Linear Mixed Models (PLMM)

$$\log(Y_i + 1) = \alpha + a_{\text{spp}[i]} + \mathbf{a^p}_{\text{spp}[i]} + b_{\text{site}[i]} + (\beta_1 + c_{\text{spp}[i]} + \mathbf{c^p}_{\text{spp}[i]}) \text{env1}_{\text{site}[i]} +$$

$$\beta_2 \text{trait1}_{\text{spp}[i]} + \beta_3 \text{env1}_{\text{site}[i]} \times \text{trait1}_{\text{spp}[i]} + e_i$$

$i: 1, 2, \dots, nm$

α, β : fixed terms

a, b, c : random terms

e : error term

$$a \sim \text{Gaussian}(\mathbf{0}, \sigma_a^2 \mathbf{I}_n)$$

$$\mathbf{a^p} \sim \text{Gaussian}(\mathbf{0}, \sigma_{ap}^2 \boldsymbol{\Sigma}_{spp})$$

$$b \sim \text{Gaussian}(\mathbf{0}, \sigma_b^2 \mathbf{I}_m)$$

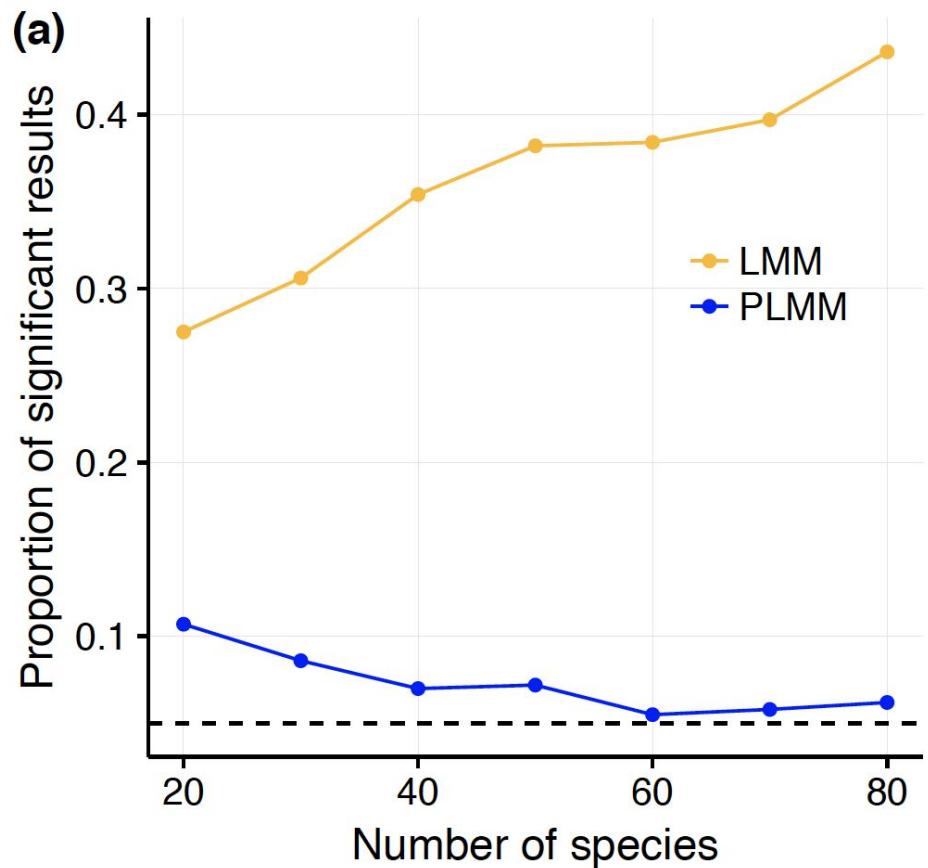
$$c \sim \text{Gaussian}(\mathbf{0}, \sigma_c^2 \mathbf{I}_n)$$

$$\mathbf{c^p} \sim \text{Gaussian}(\mathbf{0}, \sigma_{cp}^2 \boldsymbol{\Sigma}_{spp})$$

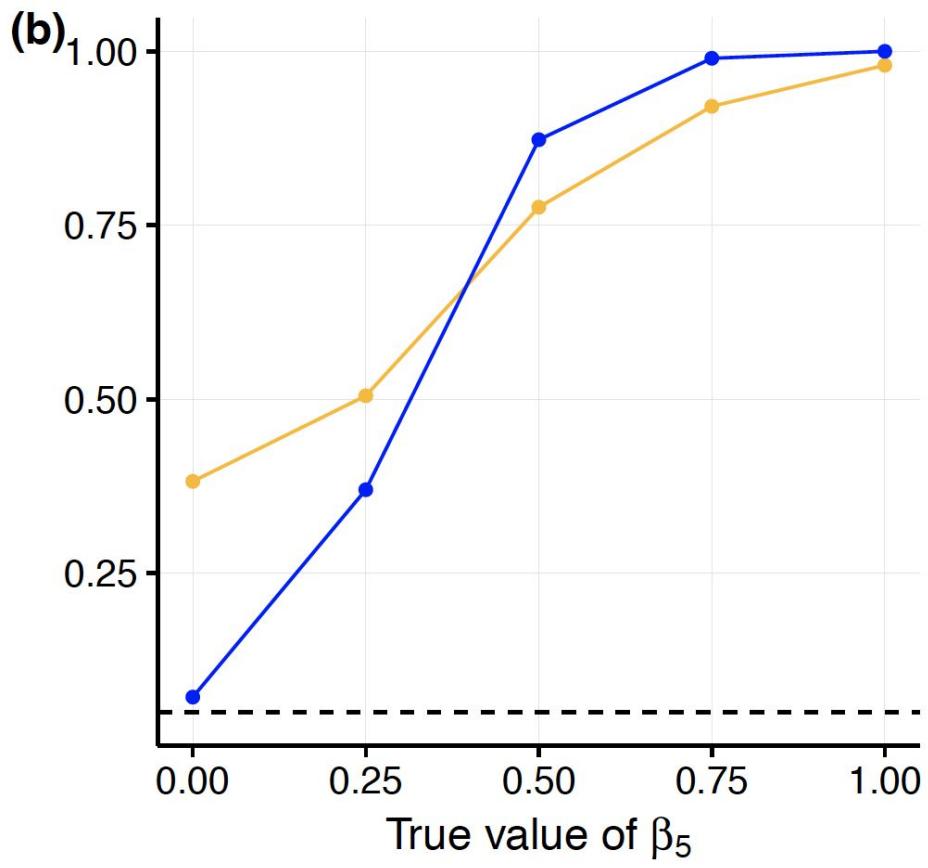
$$e \sim \text{Gaussian}(\mathbf{0}, \sigma_e^2 \mathbf{I}_{mn})$$

Phylo.
Var-Covar
matrix

Type I error



Statistical power



Functions for phylogenetic

r rpackage glmm

421 commits

Branch: master ▾ New

	daijiang update doc wi
	R
	data
	inst/extradata
	man
	src
	tests
	vignettes

phyr: Model Based Phylogenetic Analysis

A collection of functions to do model-based phylogenetic analysis. It includes functions to calculate community phylogenetic diversity, to estimate correlations among functional traits while accounting for phylogenetic relationships, and to fit phylogenetic generalized linear mixed models. The Bayesian phylogenetic generalized linear mixed models are fitted with the 'INLA' package (<<http://www.r-inla.org>>).

Version:	1.0.2
Depends:	R (\geq 3.1)
Imports:	stats, ape , Rcpp , Matrix , methods, graphics, dplyr , lme4 , nloptr , gridExtra , mvtnorm , latticeExtra
LinkingTo:	Rcpp , RcppArmadillo
Suggests:	testthat , pez , tidyR , knitr , rmarkdown , covr , picante , rbenchmark , INLA, MCMCglmm , logistf , phylolm
Published:	2019-11-13
Author:	Anthony Ives [aut], Russell Dinnage [aut], Lucas A. Nell [aut], Matthew Helmus [aut], Daijiang Li [aut, cre]
Maintainer:	Daijiang Li <daijianglee at gmail.com>
BugReports:	https://github.com/daijiang/phyr/issues
License:	GPL-3
URL:	https://github.com/daijiang/phyr/
NeedsCompilation:	yes
Materials:	README
CRAN checks:	phyr results



```
pglmm(formula = freq ~ 1 + shade + (1|sp_) + (1|site_) + (1|sp_@site_),
       data = dat,
       cov_ranef = list(sp = phylotree, site = Vspace),
       family = 'poisson', # 'binomial', 'gaussian', 'zeroinflated.binomial', etc.
       bayes = FALSE)
```

Applications of phylogenetic generalized linear mixed models

- Trait - Environment relationships
- Phylogenetic community structure
- Bipartite questions:
 - plant-pollinator
 - host-parasite

Do we miss important functional traits that can explain phylogenetic signal of species composition?

Li, Ives, & Waller, 2017, *New Phytologist*

Heuristic diagram



Measured Traits

Gaussian($\mathbf{0}$, $\text{kron}(\mathbf{I}_{site}, \sigma^2 \boldsymbol{\Sigma}_{spp})$)

$$Y = X\beta + Zu_{\text{phy-full}\{\text{Unmeasured traits}\}} + \varepsilon$$

$$Y = (X + \text{measured traits})\beta + Zu_{\text{phy-reduced}\{\text{Unmeasured traits}\}} + \varepsilon$$

$$\sigma^2 \approx 0$$

Li, Ives, & Waller, 2017, *New Phytologist*

- Random terms
- Fixed terms

Traits vs. Phylogeny

Pine barrens, WI
10 traits

~100%

Dune meadows, Netherlands
5 traits

~28%

Summary

- P(G)LMMs: better type I error control & higher statistical power
- Integrating multiple source of data
- Wide range of applications
- Get more out of community data (terrestrial or aquatic)

Research projects

1. Field research on plant community changes at the regional scale
2. Development of novel statistical models to get more out of field data
3. Analysis of big data to study global changes at the continental scale

How have global changes (climate change, land-use change, etc.) affected **functional traits** at large scale?





Plant phenology

Urbanization



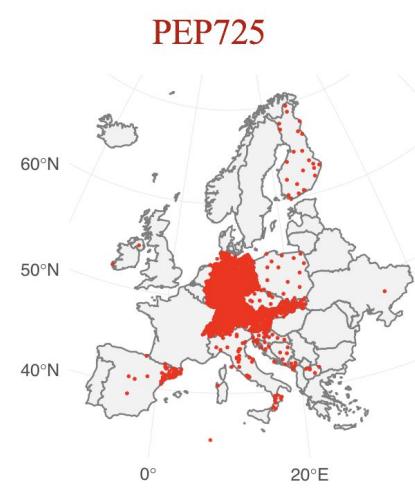
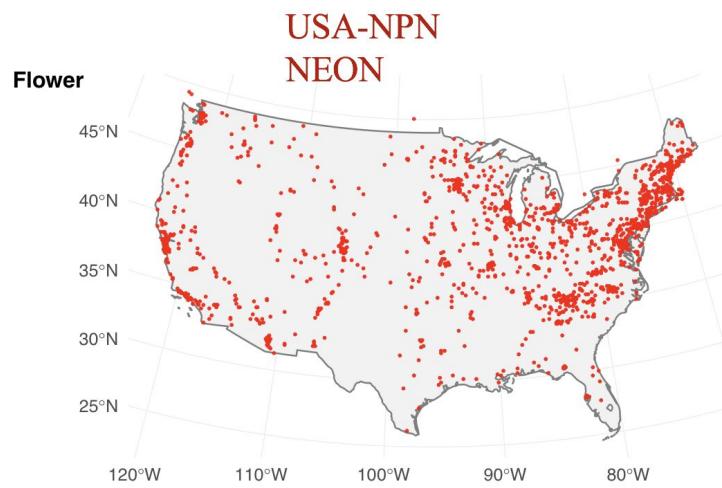
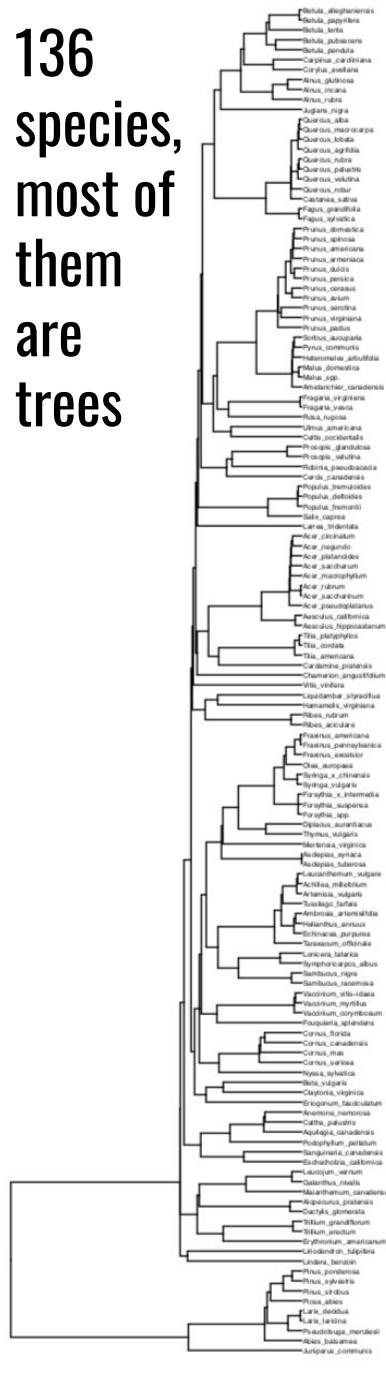
Picture from the world bank

Does the effect of **urbanization** on plant phenology vary across regions with different **climate**?

136 species, most of them are trees

Global
Data
(>22)

https://



10 km by 10 km grid cells

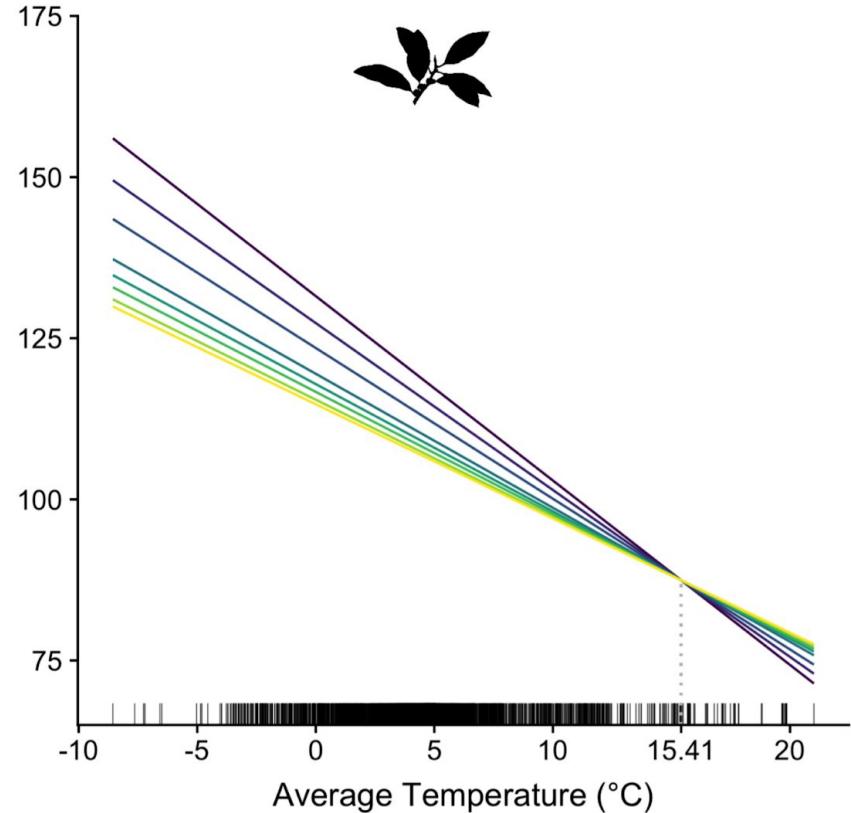
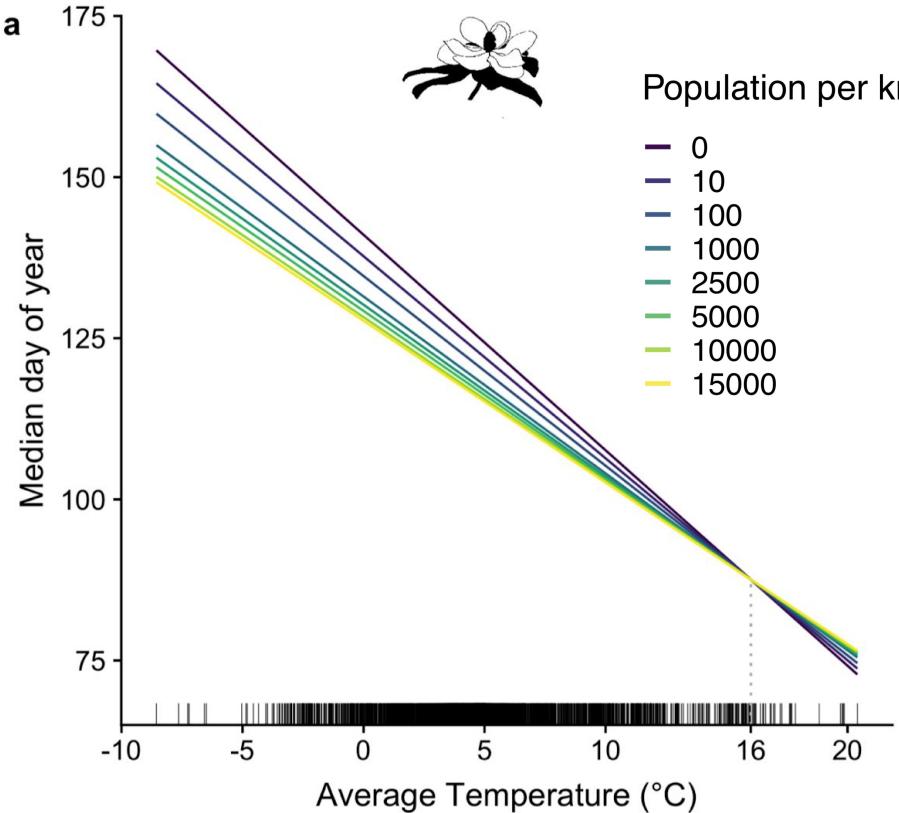
Linear Mixed Models

Median DOY of Each species (2009-2017)

~

Background Average
Temperature
(Nov.–May, 1980–2010)

Human Population Density (the 2010s, as a measure of urbanization)



The effect of urbanization on plant phenology depends on regional temperature

Daijiang Li^{1,2*}, Brian J. Stucky², John Deck³, Benjamin Baiser¹ and Robert P. Guralnick^{1,2}

Li et al. 2019,
Nature Ecology & Evolution

Summary

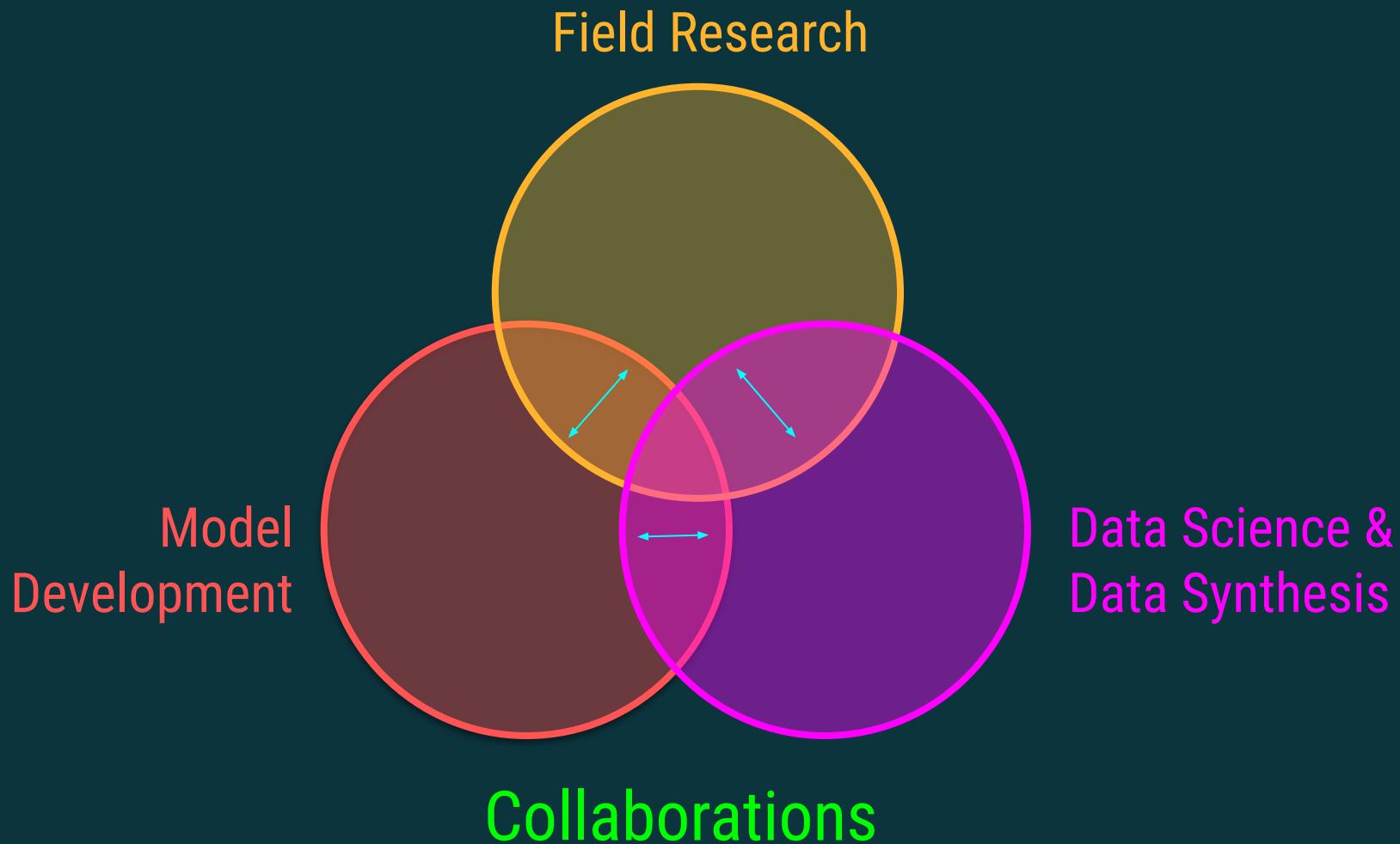
- The influence of urbanization on plant phenology varies with regional temperature
- Mechanisms?
- Including such interaction is necessary for robust understanding and accurate prediction of phenological changes (other traits?)

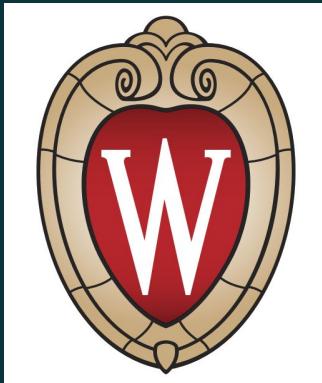
Contribution and motivation

- Investigate patterns and drivers of **long-term changes** in ecological communities
 - And other systems (e.g. Li et al. *PNAS*, 2019)
- Study **large-scale effects** of global changes on plant phenology, biological invasions, and biodiversity
 - Phylogenetic diversity (Li et al. *Proc. B* In revision);
 - Diversity-area relationships (e.g. Li et al. *Div. Distri.* 2018)
- Develop and disseminate **novel statistical methods** (e.g. R packages)
 - Evaluate and compare existing methods (e.g. Li et al. *Ecology*, 2019)

How multiple aspects of global change
have and will affect communities?

Quantitative Community Ecology Lab





Graduate School

Advancing Knowledge through Education and Research

Department of Botany



Tony Ives
Don Waller
Ben Baiser
Rob Guralnick



**Undergraduate students,
data contributors, etc.**

Collaborators:
Susan Harrison
Julian Olden
Julie Lockwood
Pamela Soltis
etc.

Thank you

