



Forecasting biodiversity reorganization with climate change

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AIST-16-0052

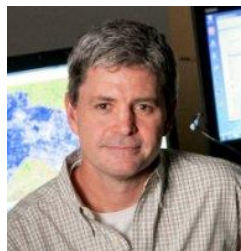
Additional funding: NSF Macrosystems Biology, NSF EAGER, NSF Community Ecology



Students and Post-Docs



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Post-Doc



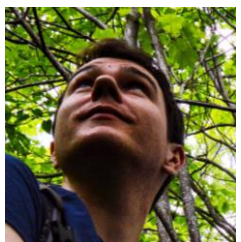
John Fay
Geospatial analyst,
programmer



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PhD student



Chase Nuñez,
PhD Student



Bradley Tomasek, PhD
Student



Taylor Minich
Master of Environmental
Management student



Christoph Hellmeyr
Post-Doc



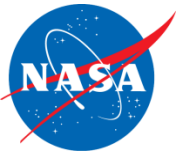
Decision-makers, scientists anticipate biodiversity change

Goals

Expand access to data and effective modeling
Automate real-time prediction

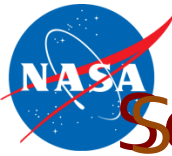
Approach

- Cloud-based predictors (climate, soils, remotely sensing), biodiversity responses (plants, birds, mammals, arthropods)
- Interactive interface
- Generalized joint attribute modeling (GJAM) analyzes community at multiple scales combined with food
- Predictive distributions/sensitivity, entire *community response*



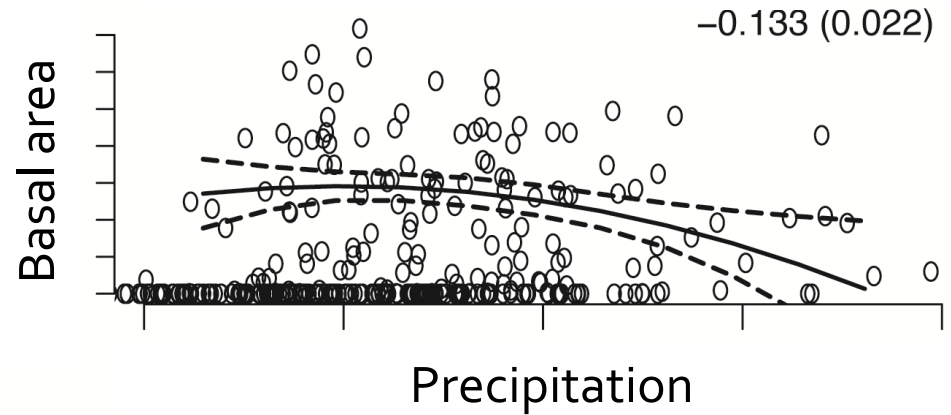
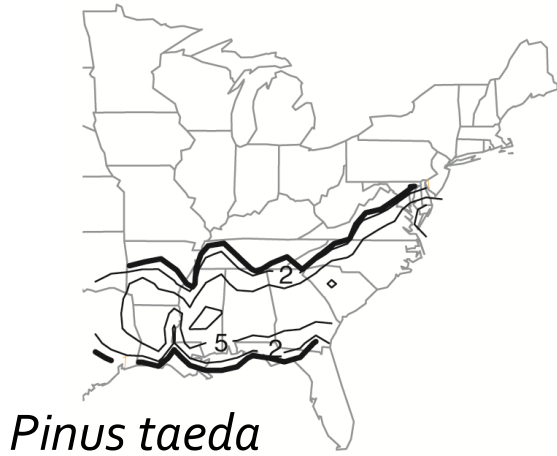
Current models provide limited guidance

- Species distribution models (SDMs), species richness models (SRMs):
 - anywhere from 0 to 50% of species at risk (Urban et al. *Science* 2015)
 - recent meta-analysis: 8%
- Scale mismatch: fit at one scale, predict at another
 - SDMs: Independent models for each species
 - SRMs: only the number of species
 - '*Simpson's Paradox*', the '*ecological fallacy*' (Clark et al. 2011)

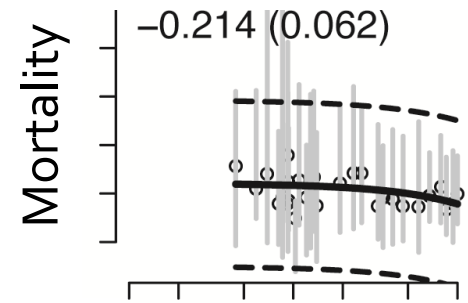
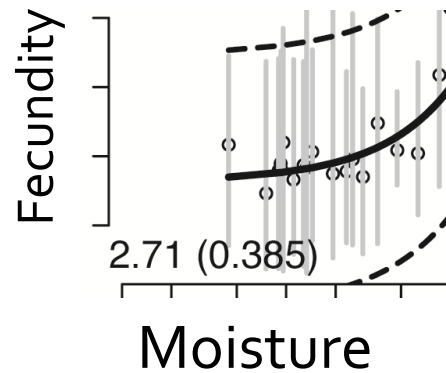
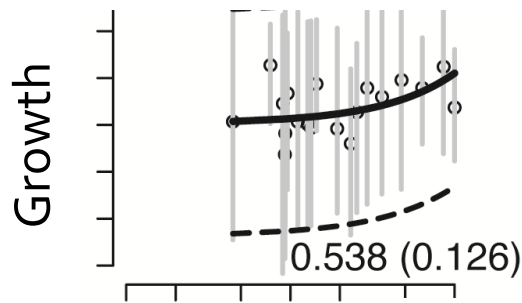


Scale: paradox benefits loblolly

Plot scale



Individual scale: moisture benefits loblolly

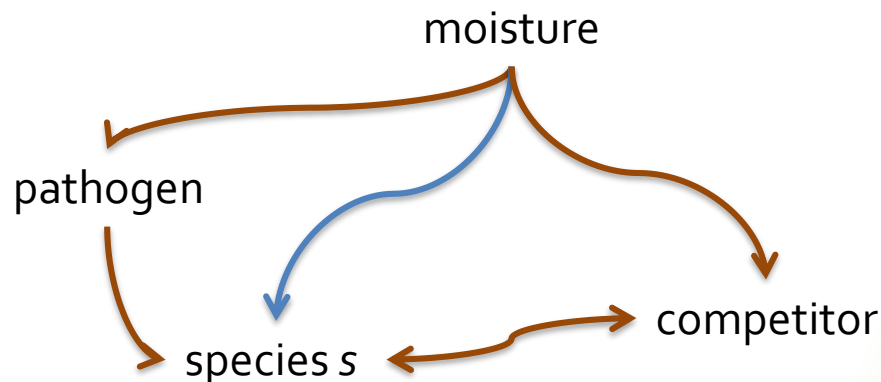




What's hard about community response?

- Data are:

- Multivariate
- Multifarious
- Median-zero



- Models are:

- Individual species
- Limited to one species group or to presence-absence
- Zero-inflated; non-linear link functions



Multifarious observations

Discrete abundance: counts

Continuous abundance: biomass, concentration

Count composition: microbiome, paleoecology

Fractional composition: satellite imagery, photoplots

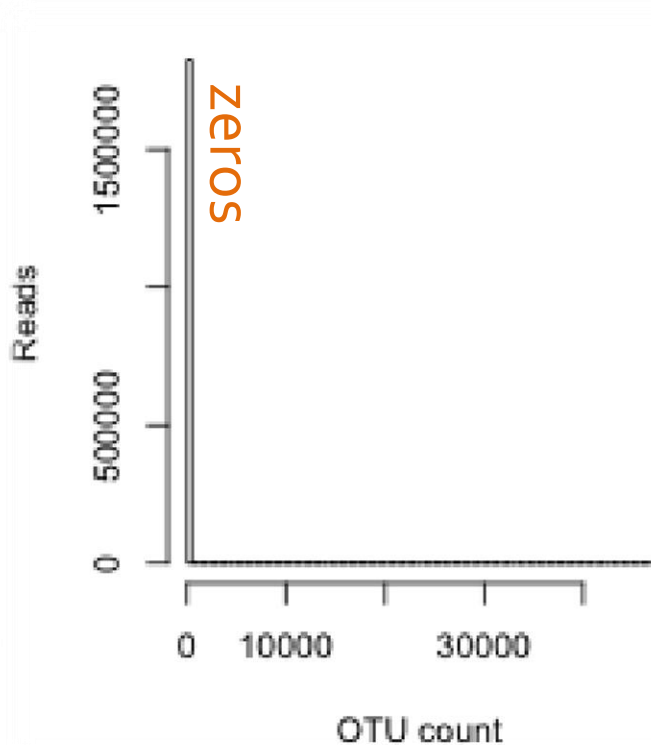
Ordinal scores: health status, phenological state

Categorical: plot status, traits

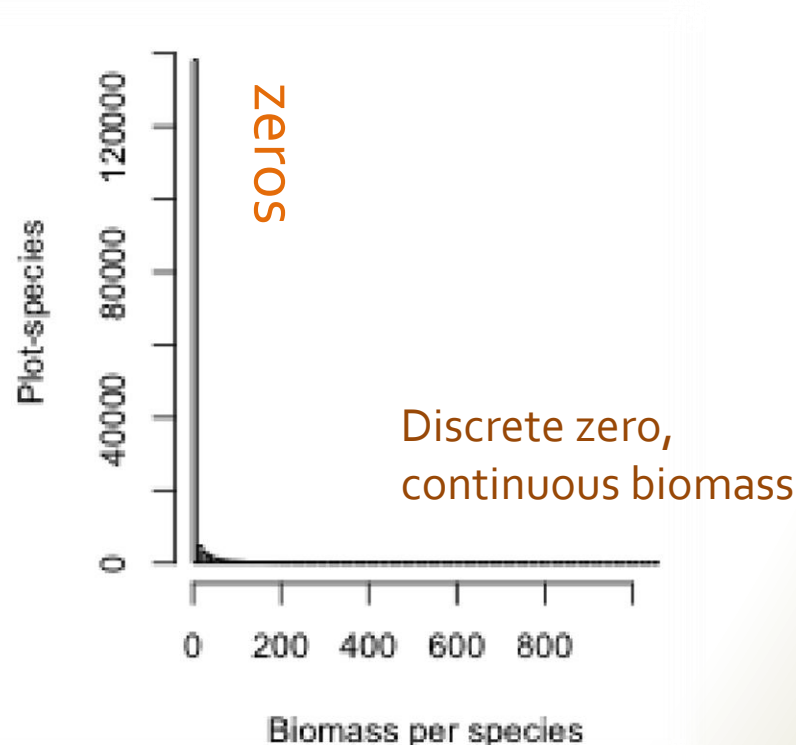


Median-zero

Endophyte microbiome



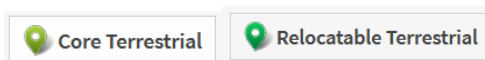
Biomass on FIA plots



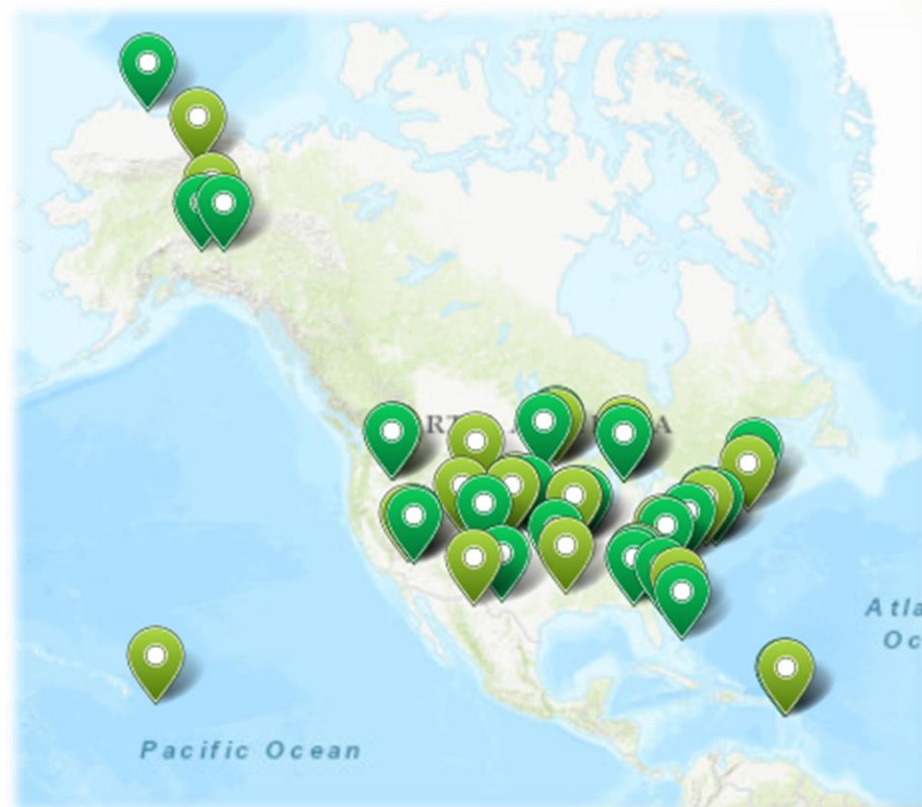
Zero-inflated models don't handle many zeros



Diverse data: National Ecological Observatory Network (NEON)



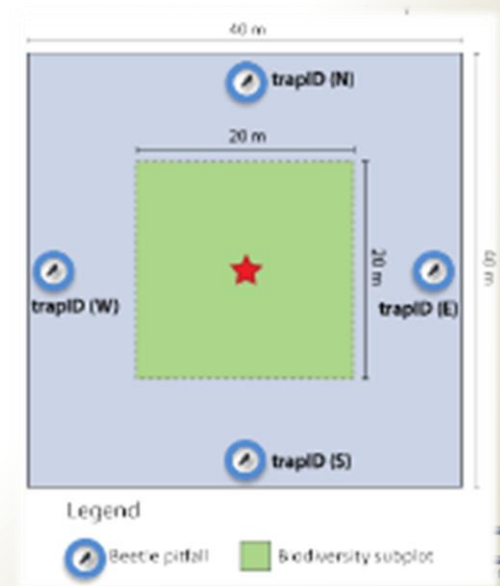
- Thousands of plots
 - Ground beetles
 - Small mammals
 - Mosquitos
 - Ticks
 - Plants
 - Birds
- Hyperspectral and LiDAR data





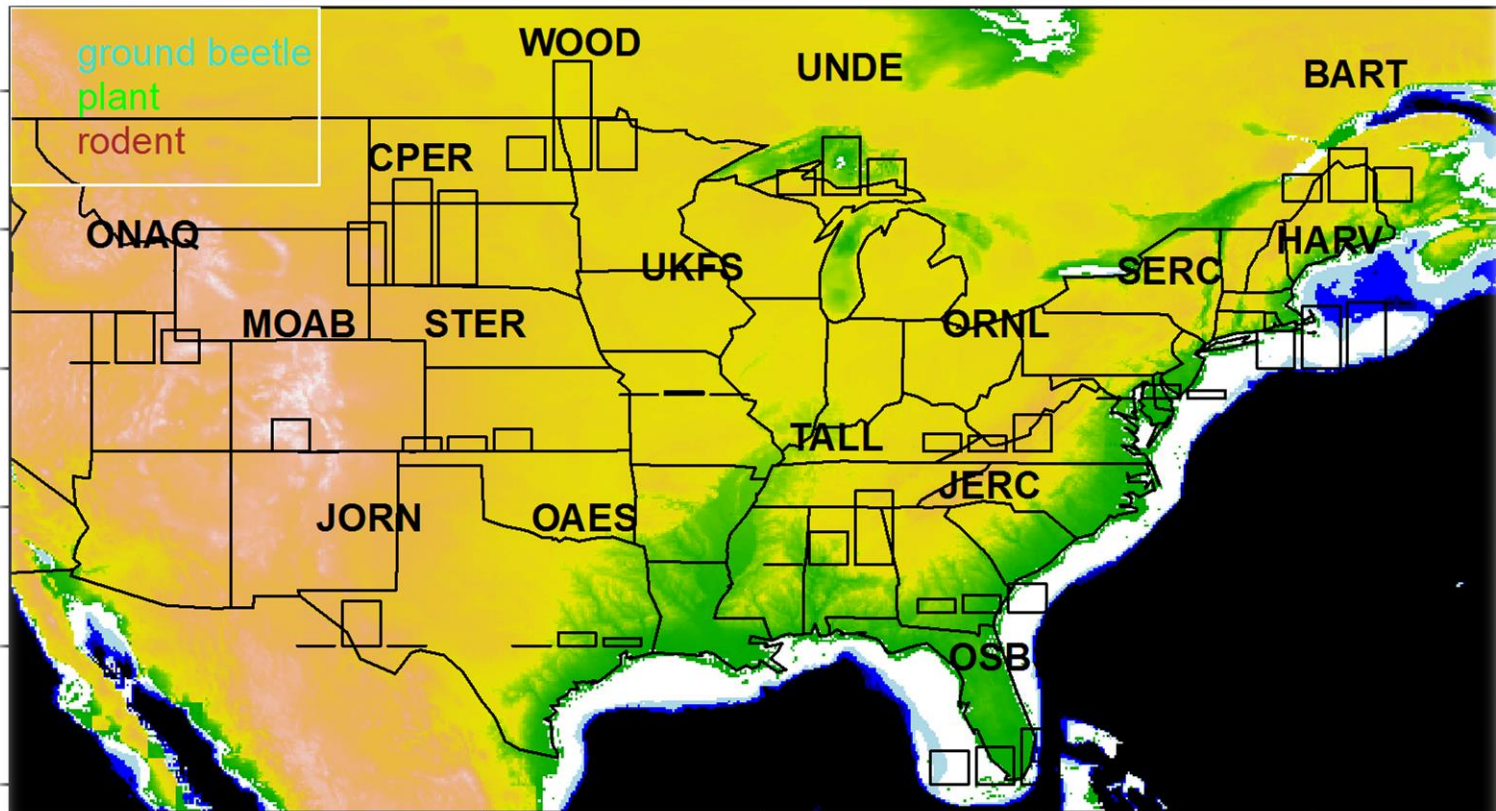
Diverse data: NEON

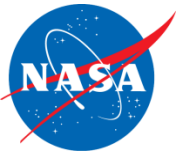
- Ground beetles – pitfall traps; **counts**
- Plant cover abundance—**percent**, censored at 0.5%
- Small mammals—**live traps; counts**
- Birds—**point counts**



Taxonomically distant species groups in NEON

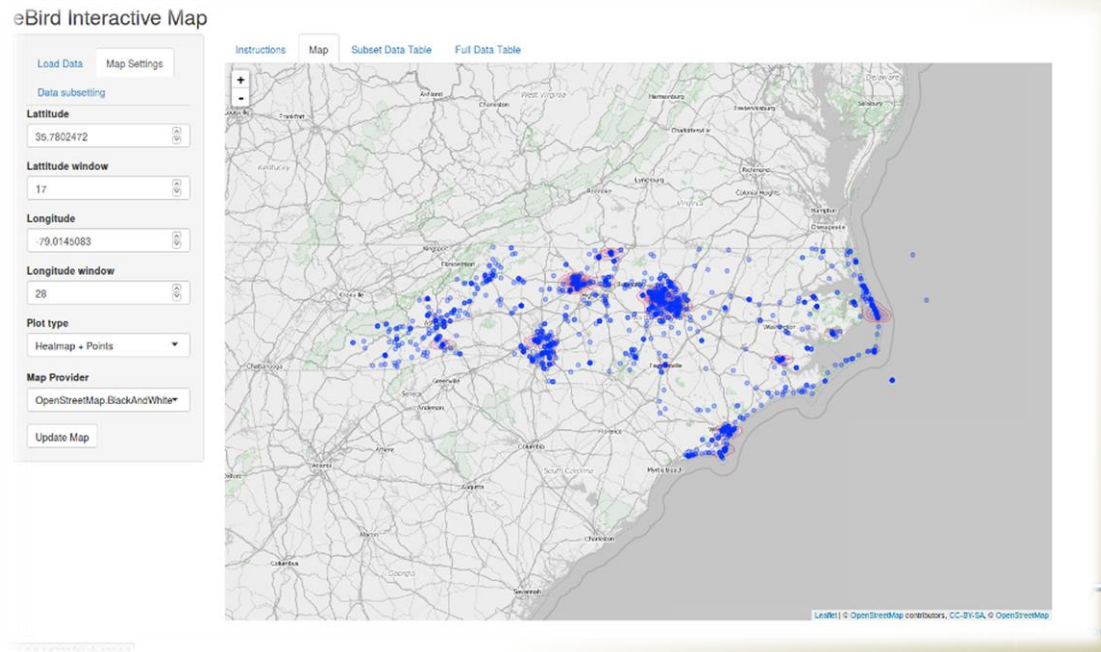
- Sampling effort/scale varies by group





Diverse data: Breeding Bird Survey (BBS) and eBird

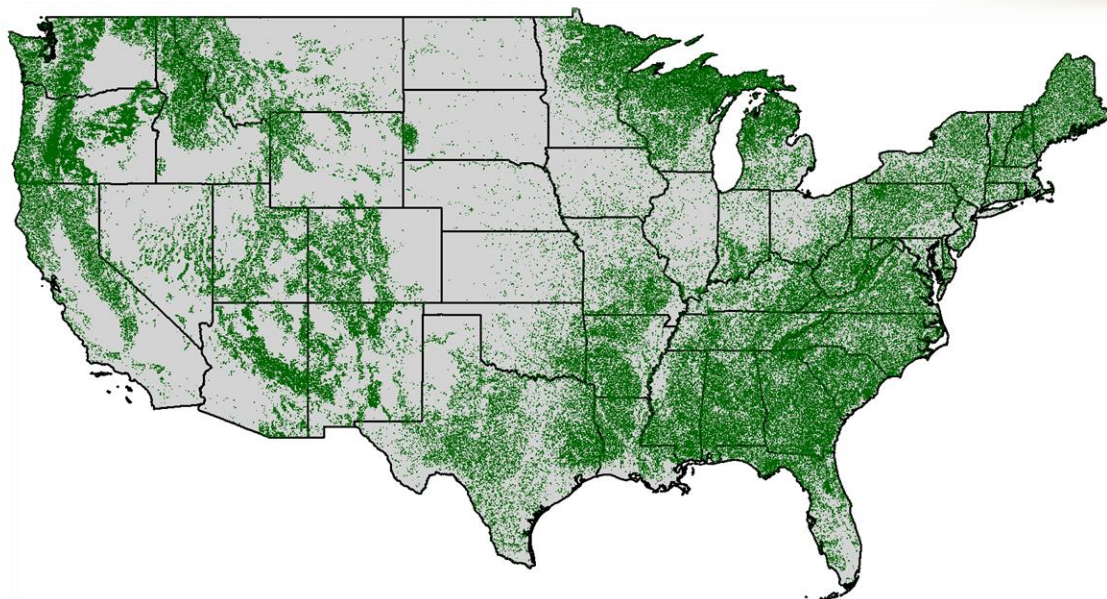
- Citizen science data
- Sampling effort available
- Sparse response (99.9% zeros)





Diverse data: US Forest Inventory Analysis (FIA) Data

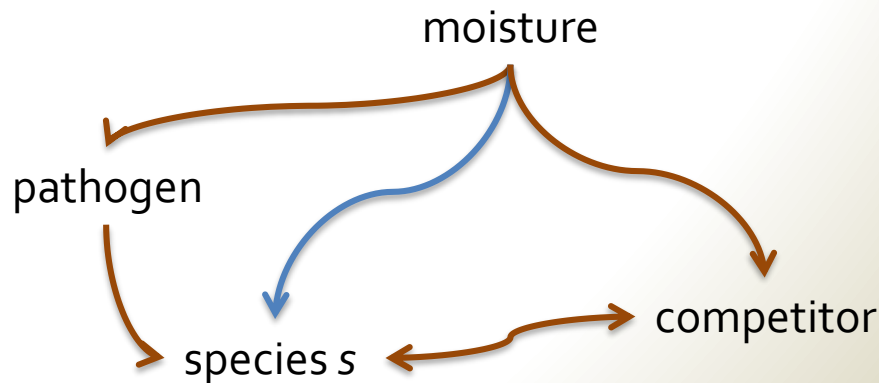
- 151,355 locations
- Millions of trees
- Plots re-censused every 5-10 years





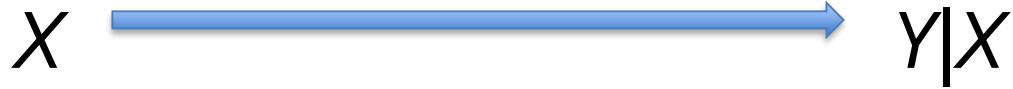
Generalized joint attribute modeling—GJAM

- **All species jointly**
 - Direct effects (main effects and interactions)
 - Indirect effects of species on one another
- On the **observation scale** (no non-linear transformations)
- **Massive zeros**
- **Generative:**
 - predict communities given environment
 - inversely, environment given community (i.e. *fingerprinting*)





Standard approach (e.g., glm,...)

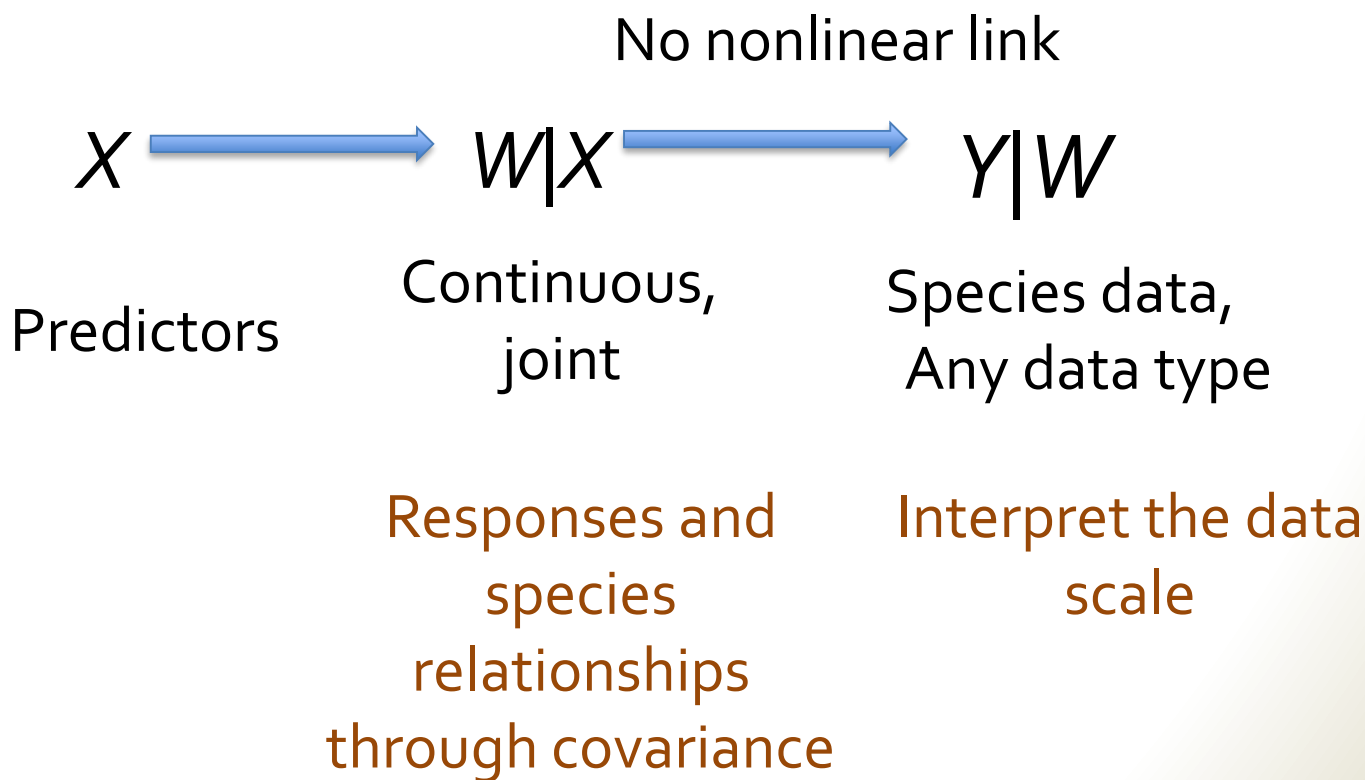


Predictors

Species data,
Continuous or
non-linear link



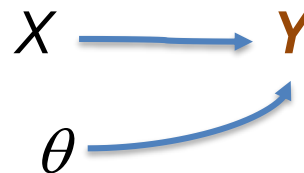
gjam idea





Role of prediction

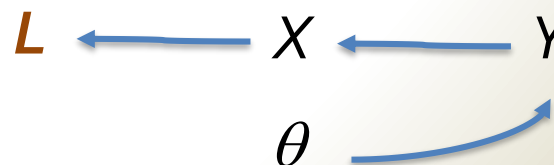
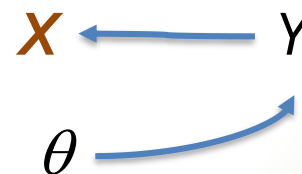
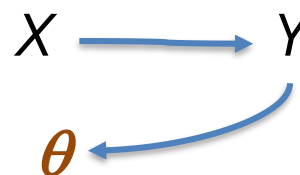
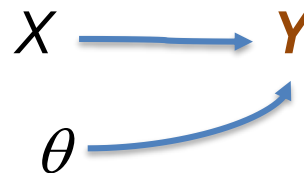
- Generative model
 - *Predict the fitted data?*





Role of prediction

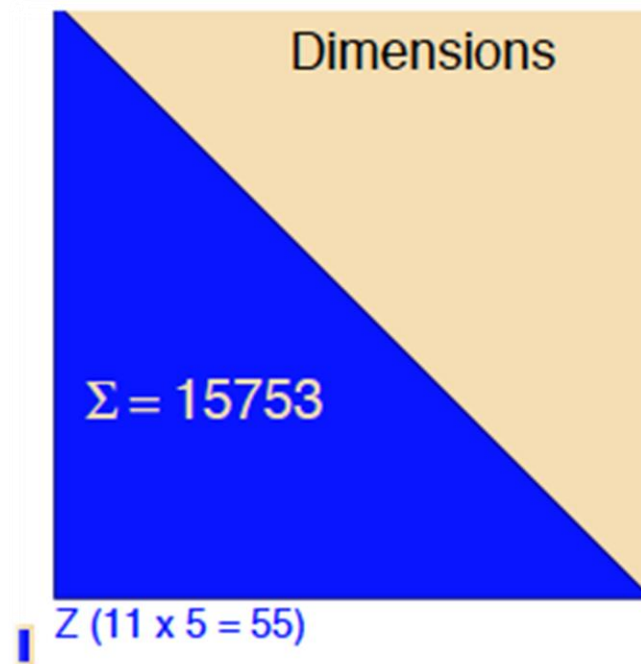
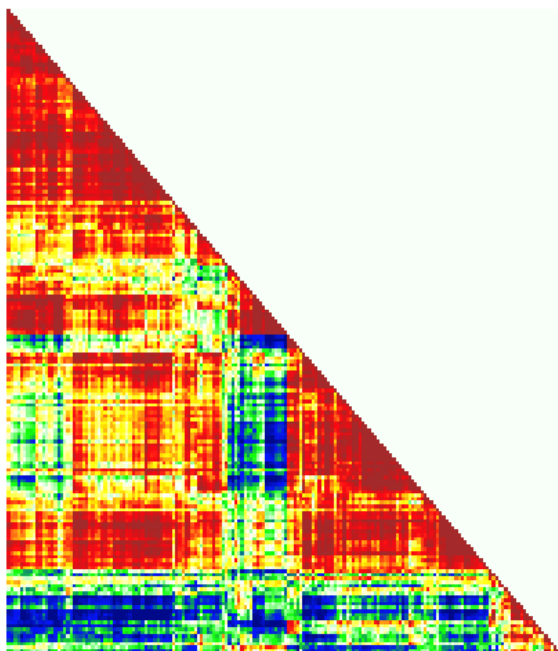
- Generative model
 - *Predict the fitted data?*
- Parameter estimation
 - *Sensitivity*
- Inverse prediction
 - *Environmental fingerprint*
- Location fingerprint
 - *Location uniquely determines community?*





Dimension reduction

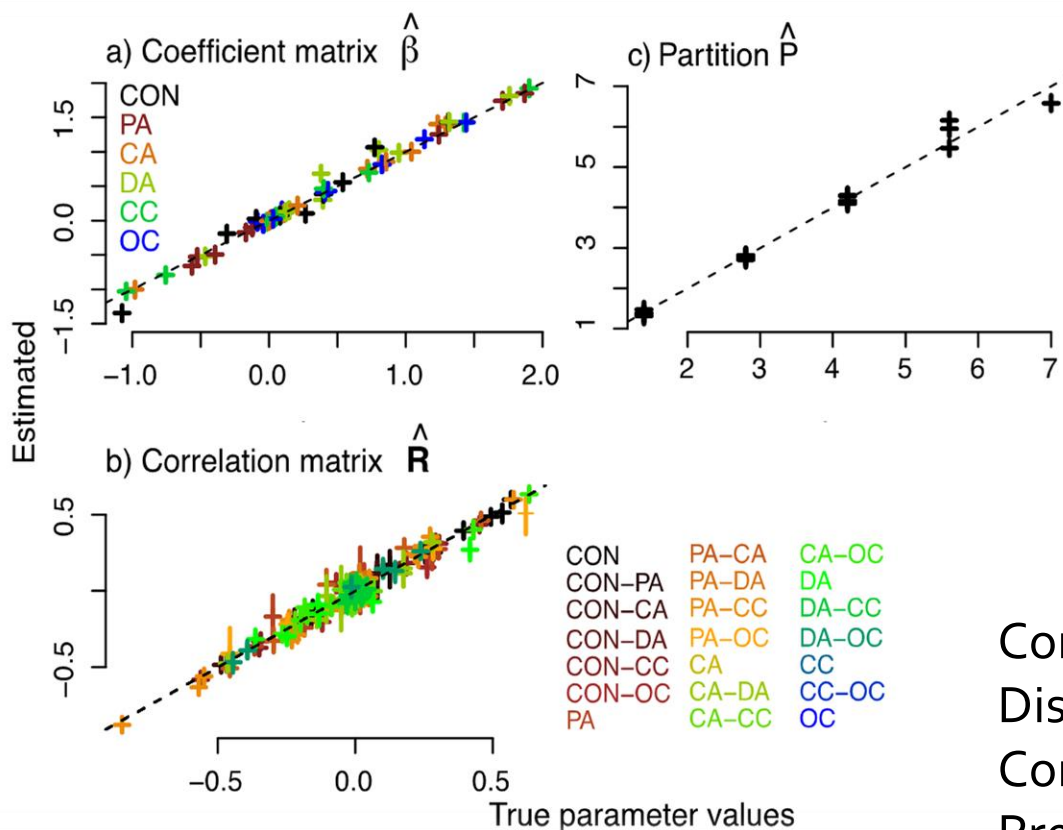
- 10^2 species means 10^4 parameters



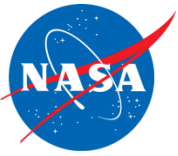


Parameter recovery in simulation

Combine all data types



Continuous (CON)
Discrete abundance (DA)
Continuous abundance (CON)
Presence-absence (PA)
Composition count (CC)
Ordinal count (OC)



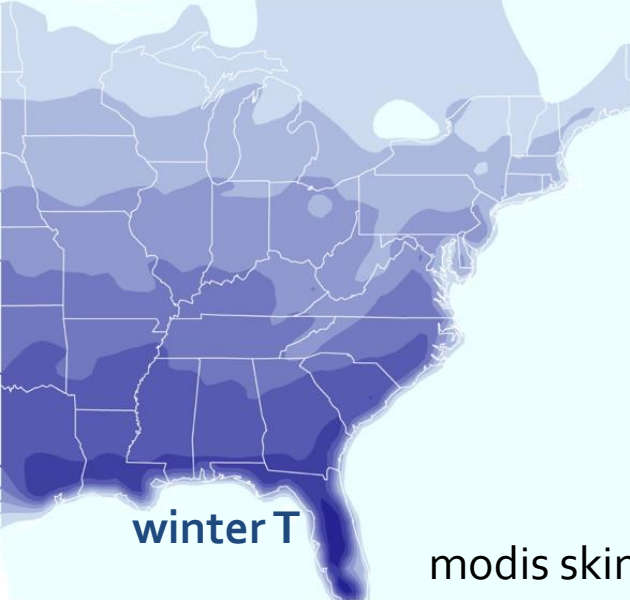
Why is GJAM model-based?

- **Generative** for community
 - Model-based sensitivity, uncertainty
- **Combine data** types; **uneven effort**
- **High-dimensional** (1000 species/OTUs)
 - Model-based aggregation
- Estimates on the **observation scale** (no non-linear link)
- Accurate **prediction**
 - **Forward**: $X \rightarrow Y$
 - **Inverse**: $X \leftarrow Y$
 - Map **fingerprint**: $L \leftarrow X \leftarrow Y$

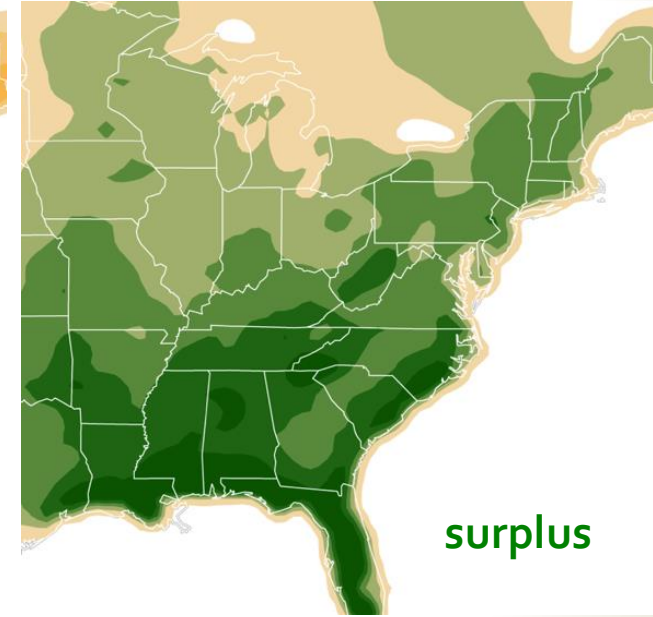
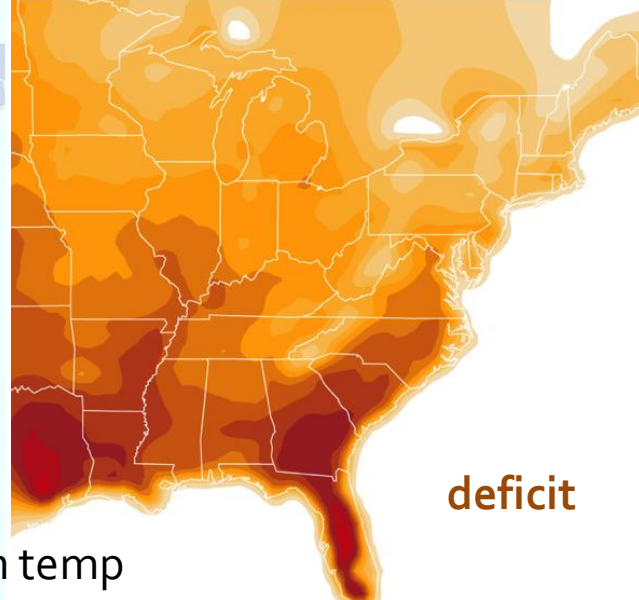


GJAM for the joint community

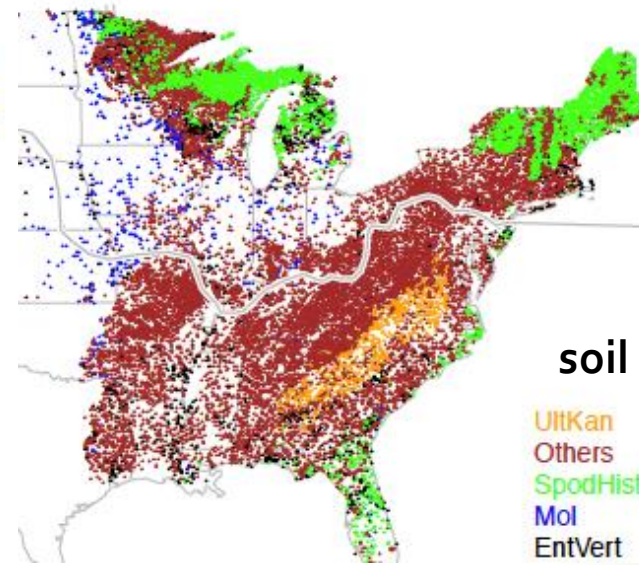
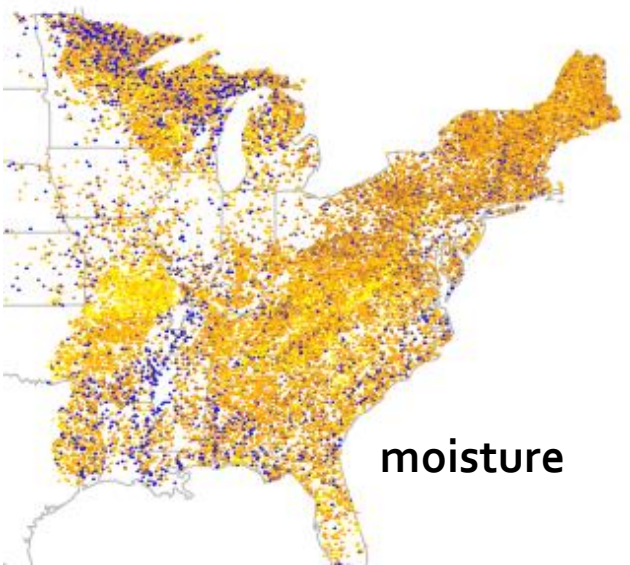
- *Application at NEON*
 - Which species are sensitive?
 - Environment and location fingerprints
 - Community change



modis skin temp



Cloud-based predictors of biodiversity change





Tutorials for data acquisition in GEE

- Environmental and remote sensing data
- Simple inputs:
 - dataset
 - metric of interest
 - temporal/spatial averaging

Functions to pull variables from GEE

This workbook provides an example for how to obtain environmental covariate data from Google Earth Engine. These functions can calculate environmental data (1) at a point, (2) a spatial average within a buffer around a point, or (3) a spatial average within a polygon

We have also created a PDF for how to download/install python, jupyter notebooks, and the GEE python API. Please see [Part1_Installing_GEE_API_tutorial.pdf](#). This pdf is based off the tutorial found here: <https://github.com/earthlab/tutorials/blob/master/documentation/intro-google-earth-engine-python-api.md>

The first step is to import the functions saved in `pullGEEvar.py`. In this document, we'll walk through a few examples for how to download environmental data related to land cover, topography, soils and climate.

Add a folder called "layers_gjam" to your google drive. If you want to save files in an alternative folder on your google drive, then you will need to specify a different name for `folderOut`, default is "layers_gjam".

If you would like to use your own dataset, you can either email me with a shapefile (amanda.schwantes@duke.edu), and I can add it to my assets folder. Or you could upload the shapefile to your assets folder, and then use the optional parameter "username" to specify your username. The ID field for all these files is `geeID`. Please add an ID column to your shapefile with the name "geeID" before you upload your file to your assets folder. Each row must have a unique ID.

Land cover

GEEtcPts: Calculates percent tree cover
GEEicPts: Calculates percent impervious cover
GEElcPts: Calculates land cover value at a point or a frequency table of land cover types within a polygon or buffer from a point

Below we provide an example for GEEtcPts, but these three functions work in the same way.

```
In [ ]: from pullGEEvar import GEEtcPts
        help(GEEtcPts)

In [ ]: GEEtcPts('example', 2011, 0, 0)
```




Automated workflows download/preprocess

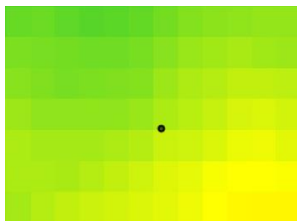
- Geospatial climate, landscape variables
 - Climate: precipitation, PET, temperature, water deficit, VPD
 - Topography: slope, elevation, aspect
 - Soils: available water storage, % sand, % clay, ...
 - Land cover
- Remote sensing
 - MODIS: LST, ET, GPP, LAI, EVI/NDVI, phenology
 - SMOS: soil moisture
 - Landsat: vegetation and water indices
 - Lidar



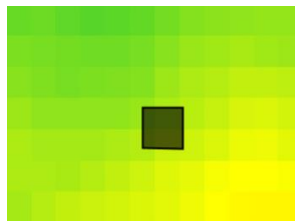
Cloud Computing

- Processing with GEE python API cloud-computing platform
 - Efficient pre-processing (e.g., filtering with QC bands from MODIS, Landsat products)
 - Temporal averaging: months, seasons, years
 - Spatial averaging: points, plots/grids, points with buffers

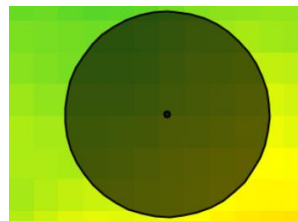
point

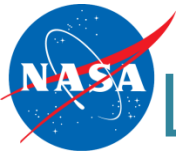


plot



Buffer from point

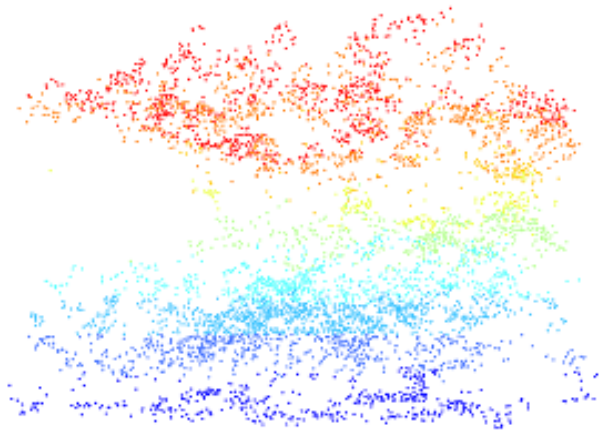




Lidar: habitat structure

- Data processed for 2017, ~3,000 plots, 39 sites
- Habitat structure metrics

Height (m)



Plot HARV34:

relief ratio: 0.52

max height: 29.5

mean height: 15.2 ± 9.5

Plot HARV36:

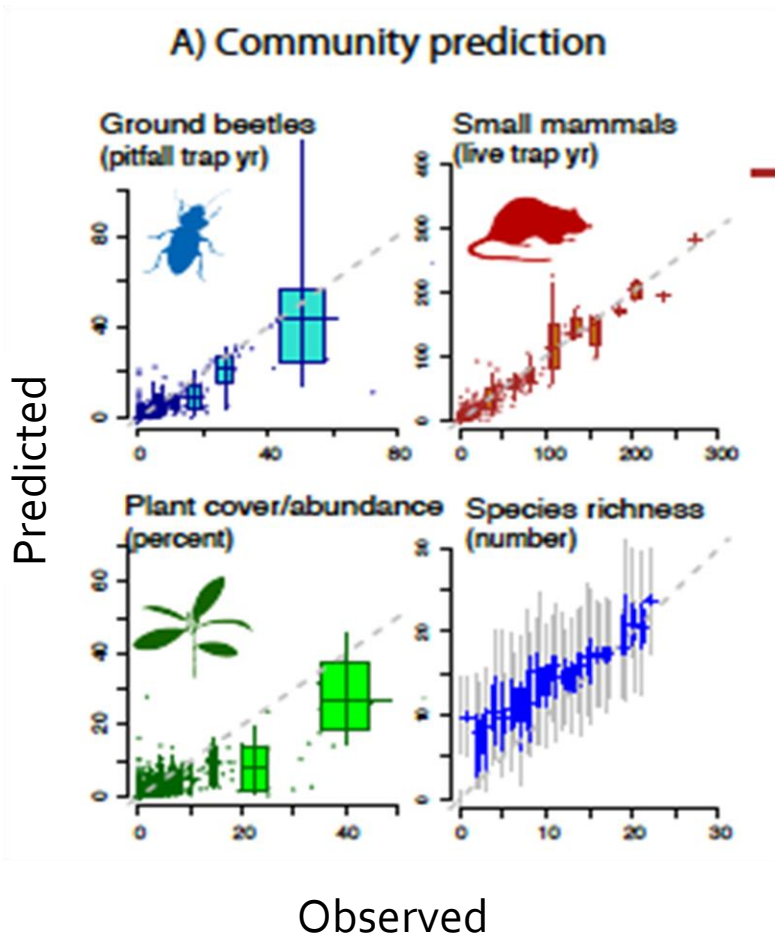
0.76

29.1

22.4 ± 6.5



Precision prediction: *one distribution for all species*

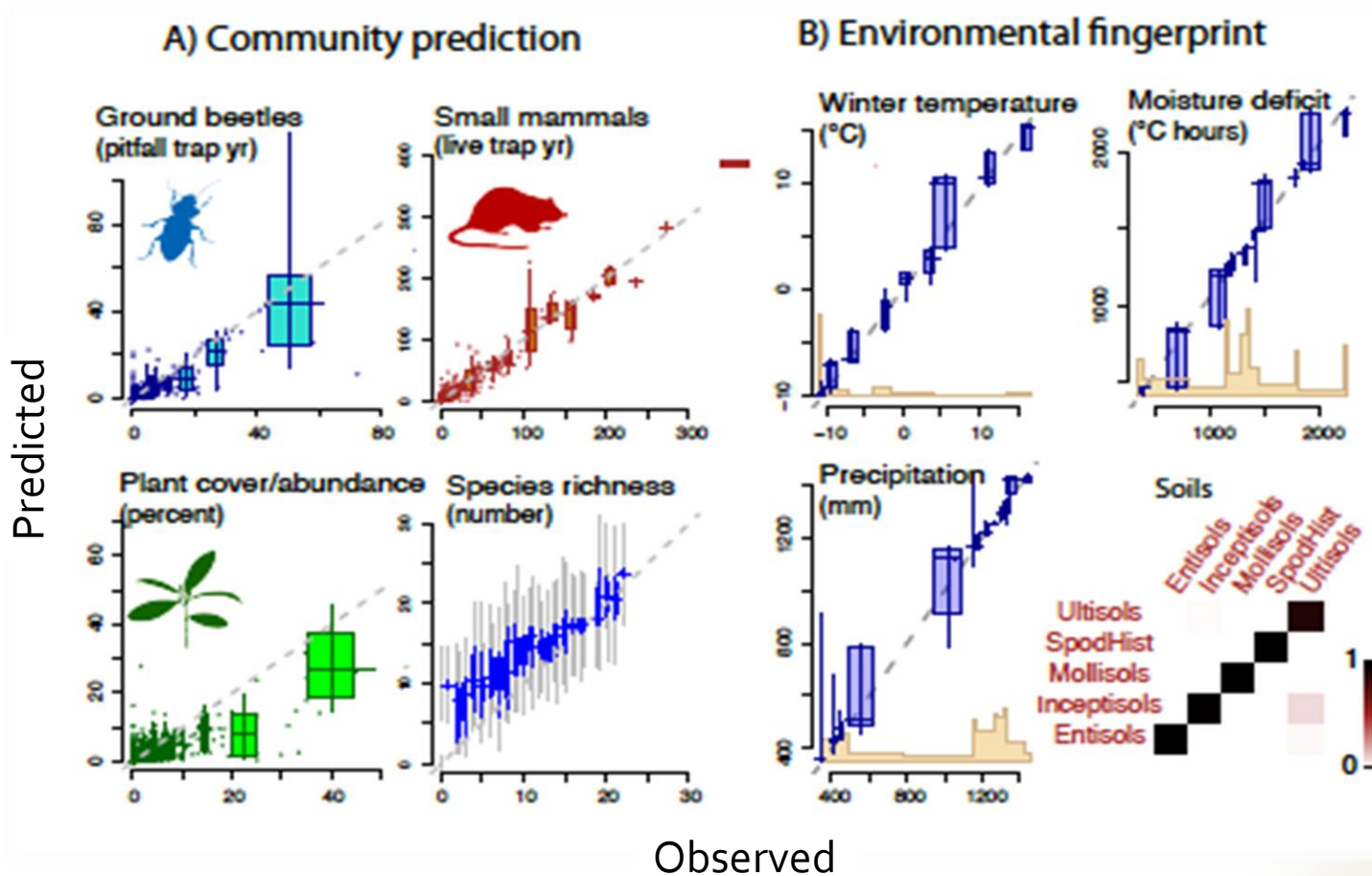


- Taxonomically diverse species groups

Ground beetle pitfall
Plant cover plot
rodent live trap



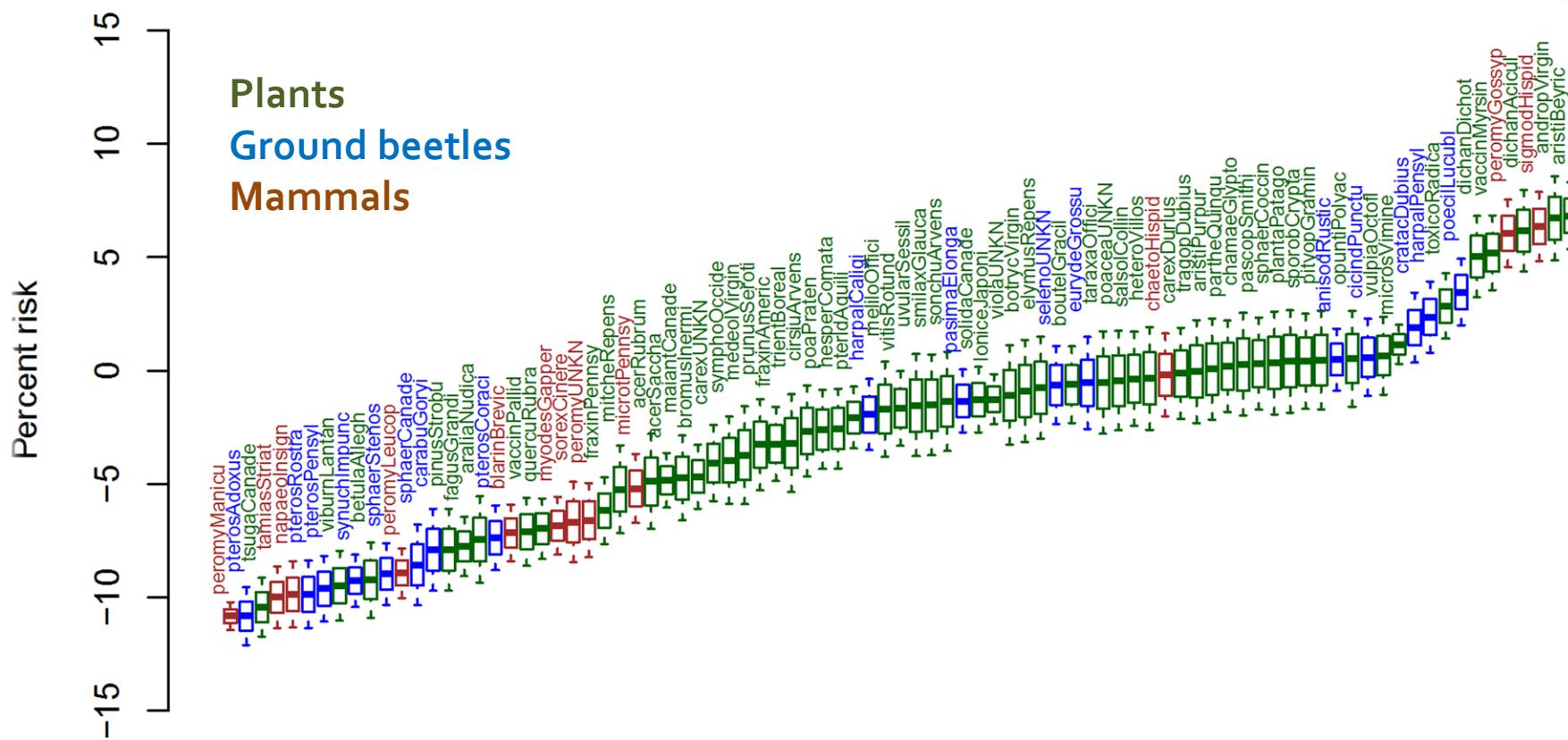
The community 'fingerprints' its environment...





Species at risk with +2°C

- The value of a generative model-based



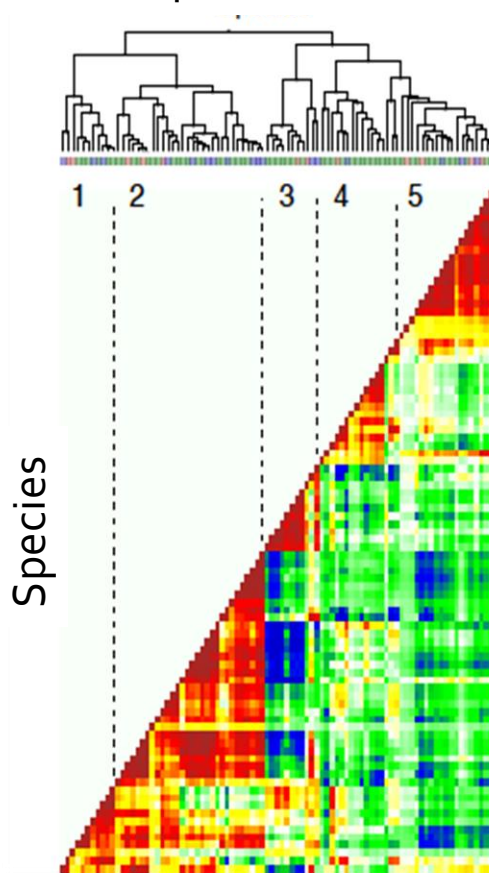


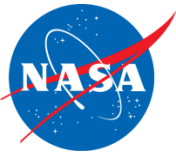
Communities defined by response to the environment

- *left: communities defined by response*

Response community

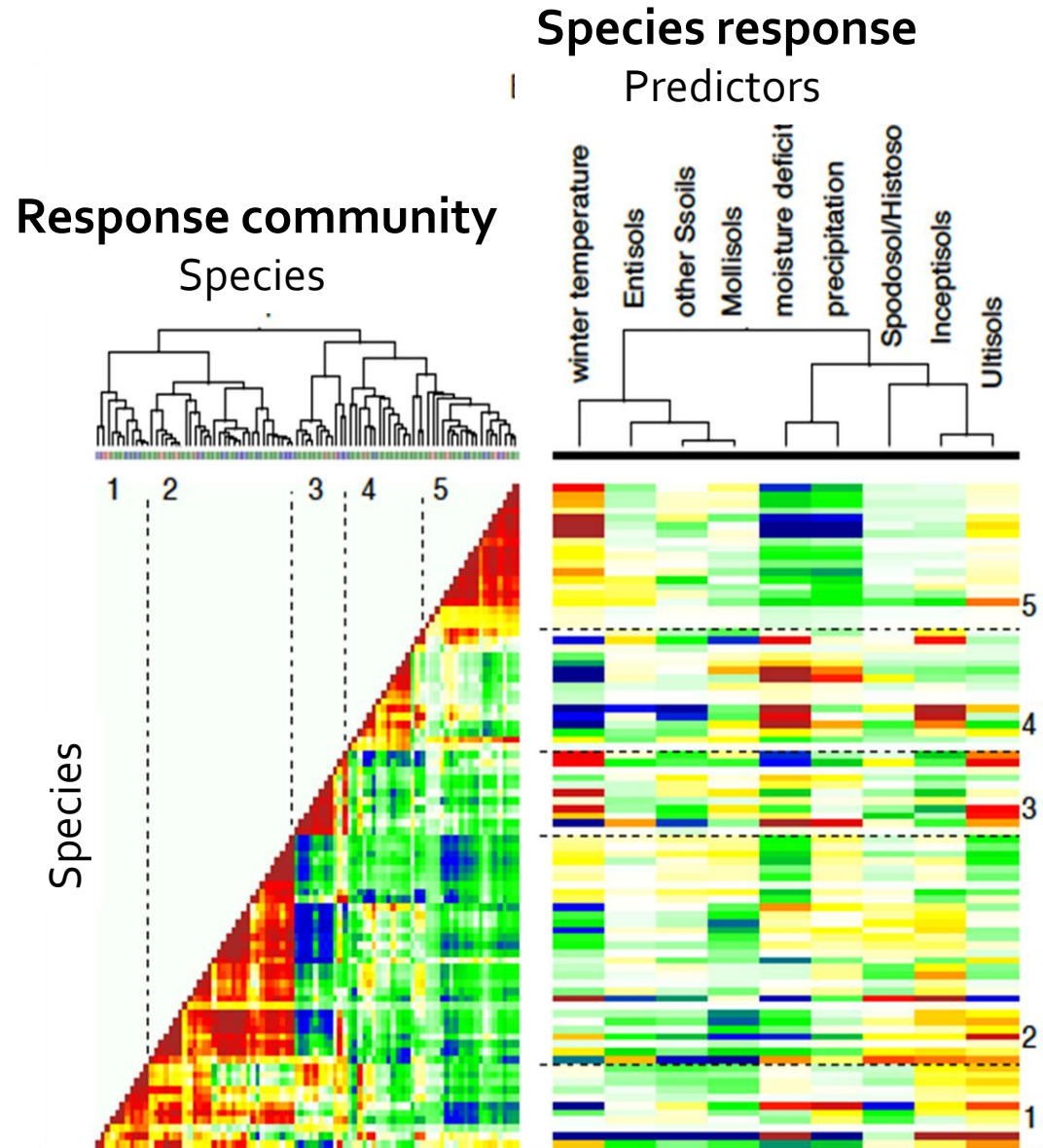
Species





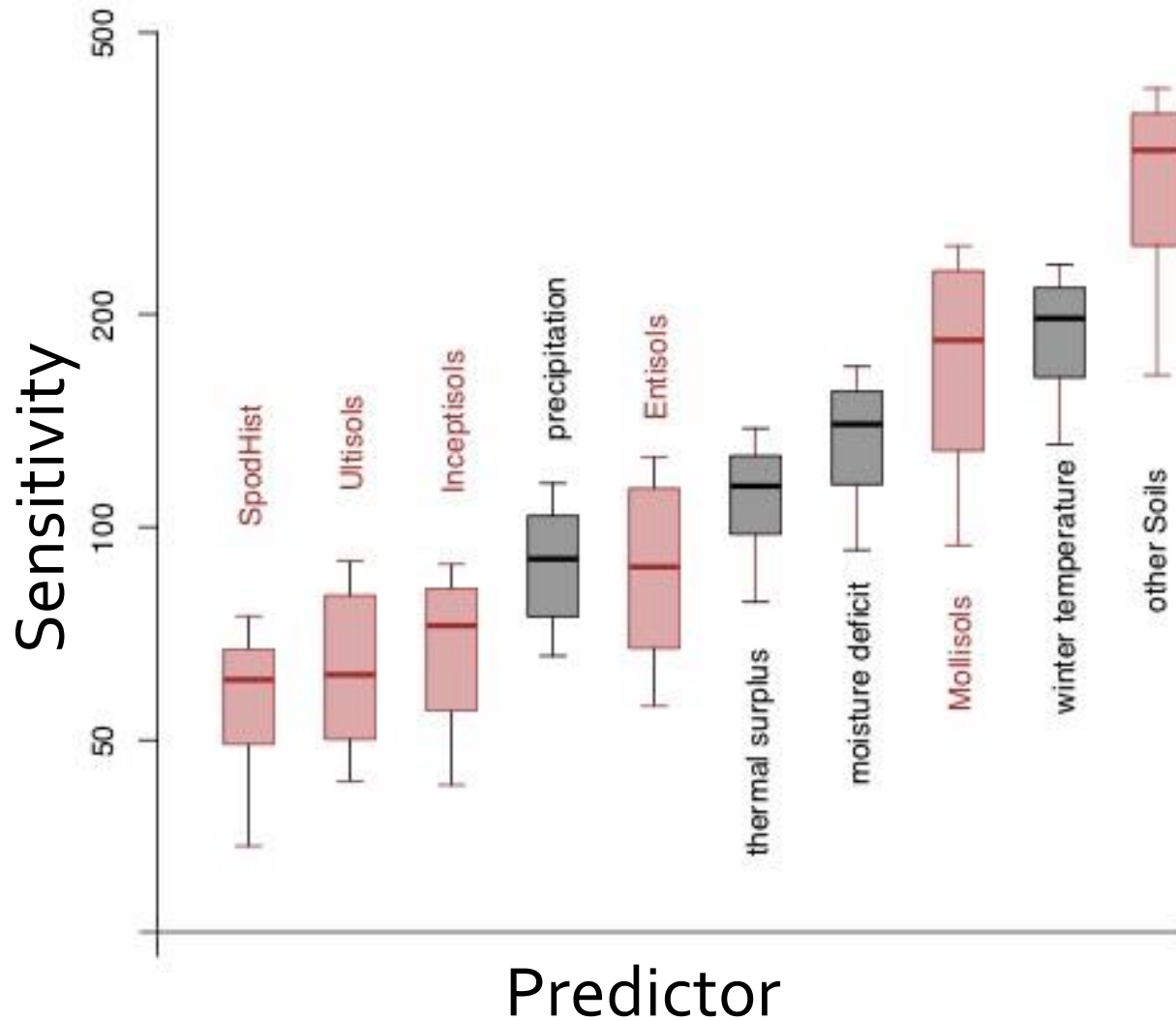
Communities defined by response to the environment

- *left: communities defined by response*
- *right: species by environment responses*





Community-wide effects





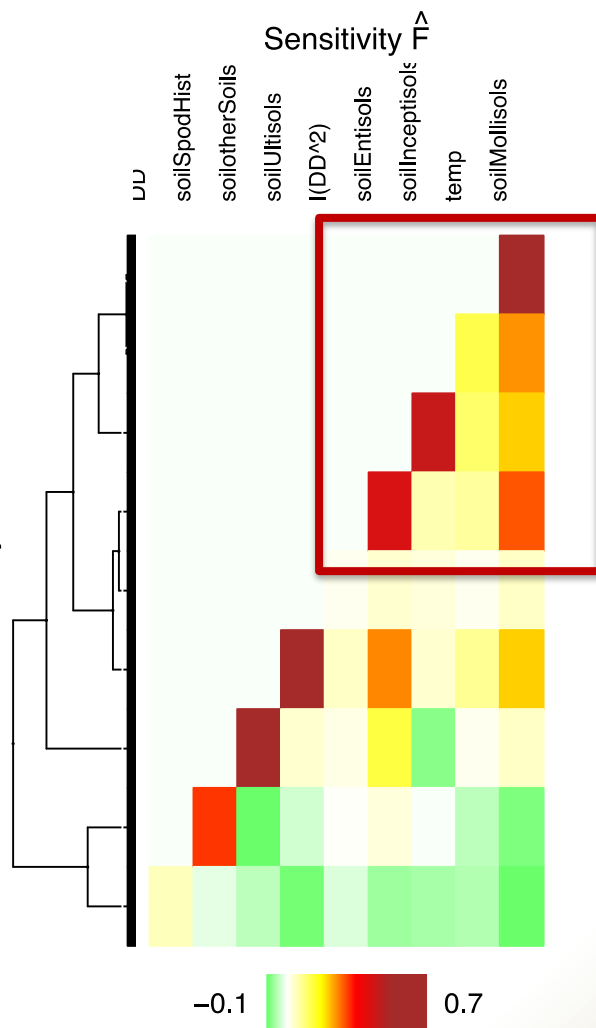
Environment defined by effect on community

Community effect

Predictors

Species response

- *left: predictors defined by effect*



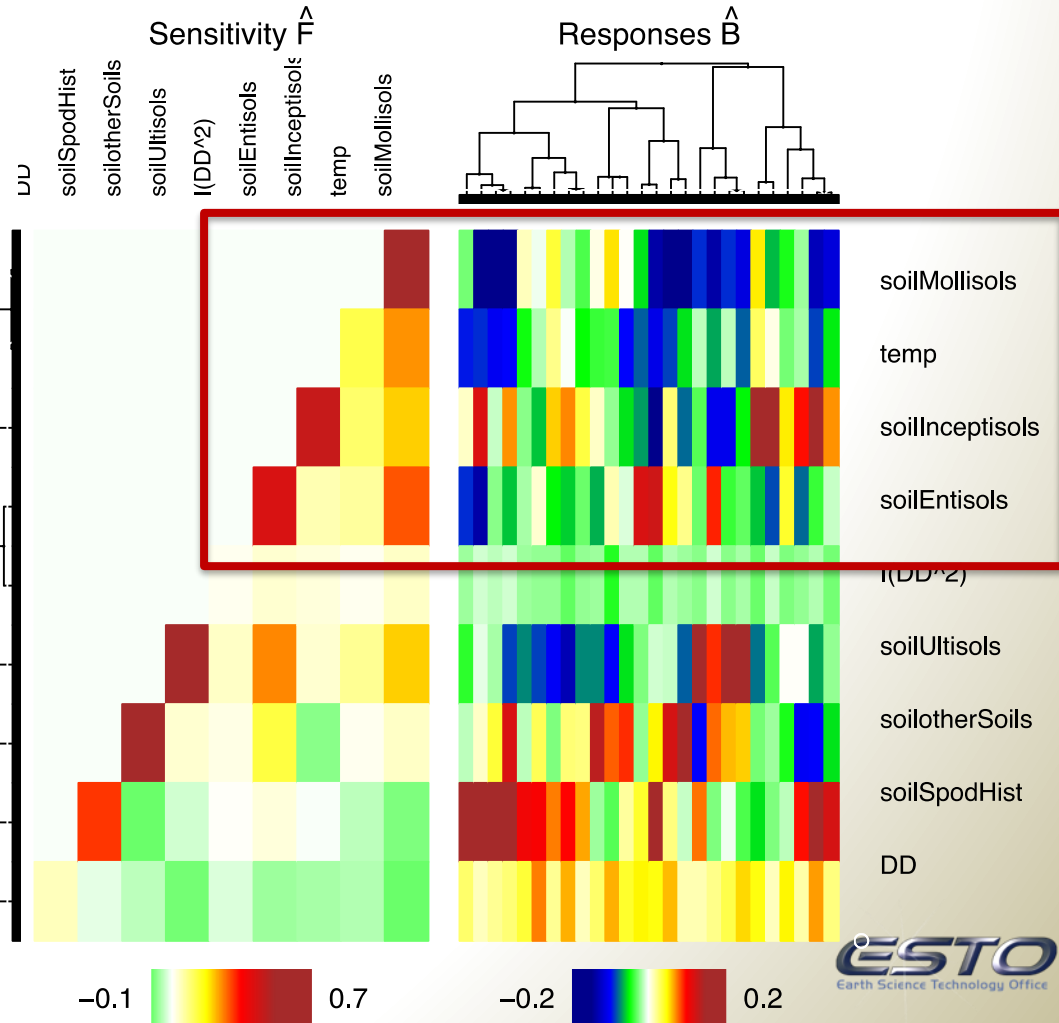


Environment defined by effect on community

Community effect

Predictors

Species response



- *left: predictors defined by effect*

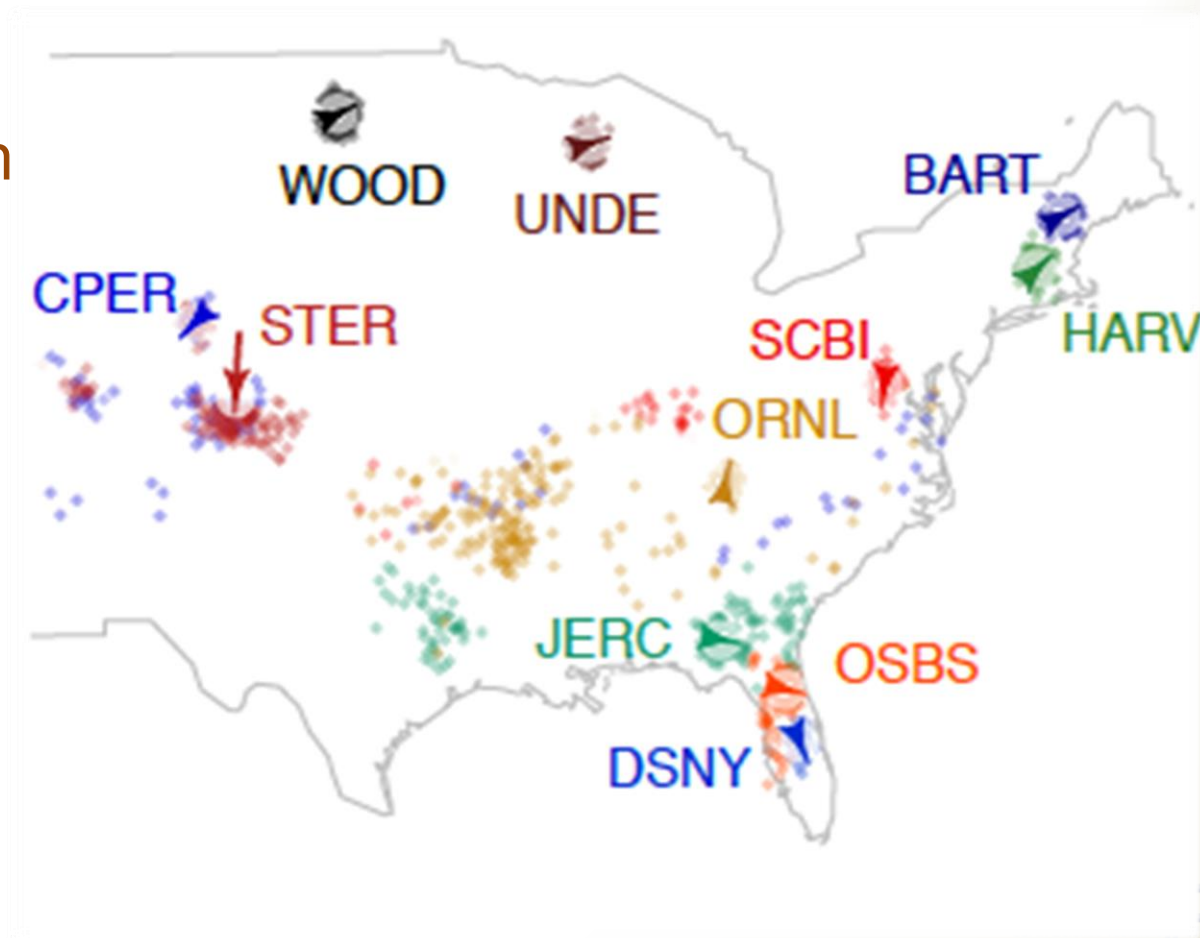
- *right: species by environment responses*



Location fingerprint

the community knows its location

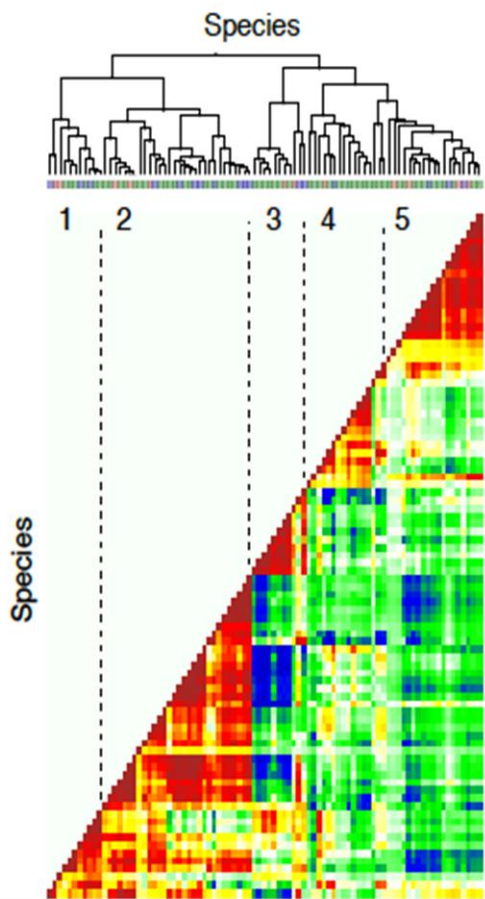
Arrows point from true sample location to predicted sample location





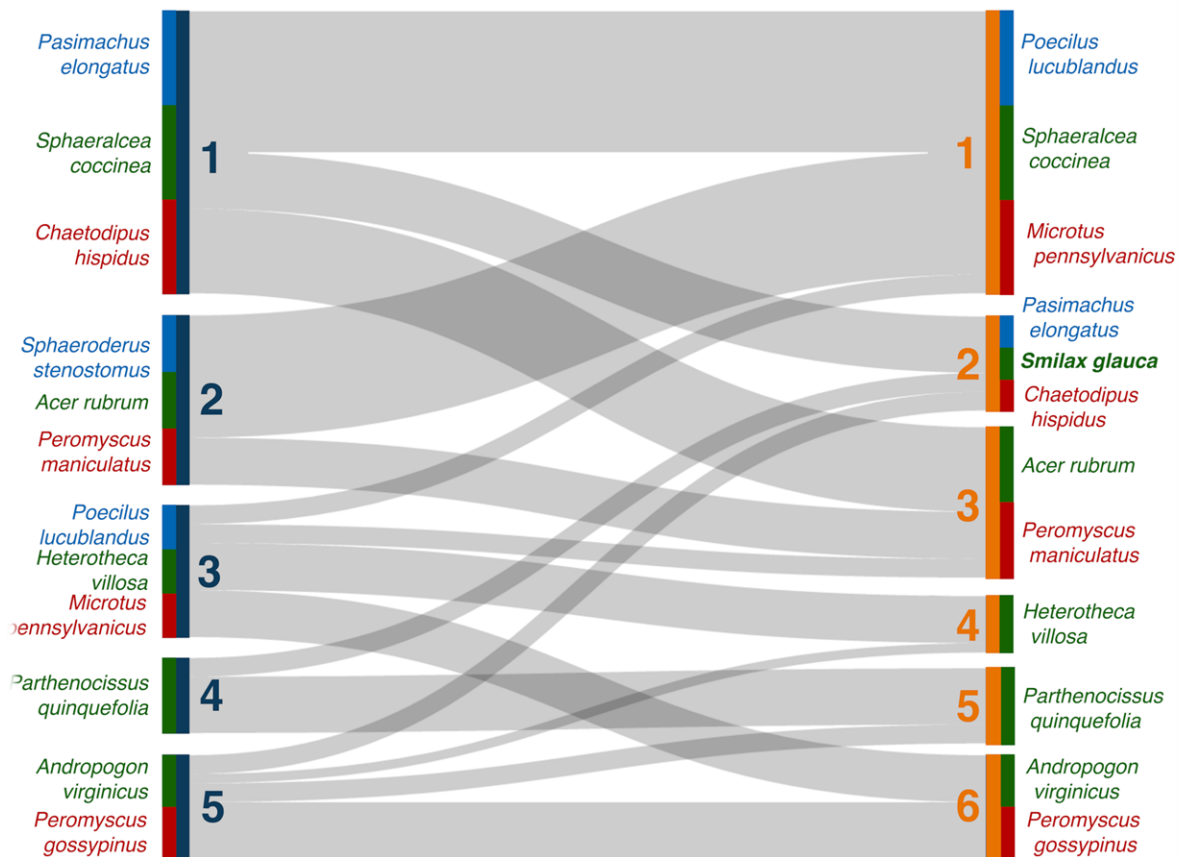
+2°C: Community reorganization

A) Response community \hat{E}



Current Climate

+2°C



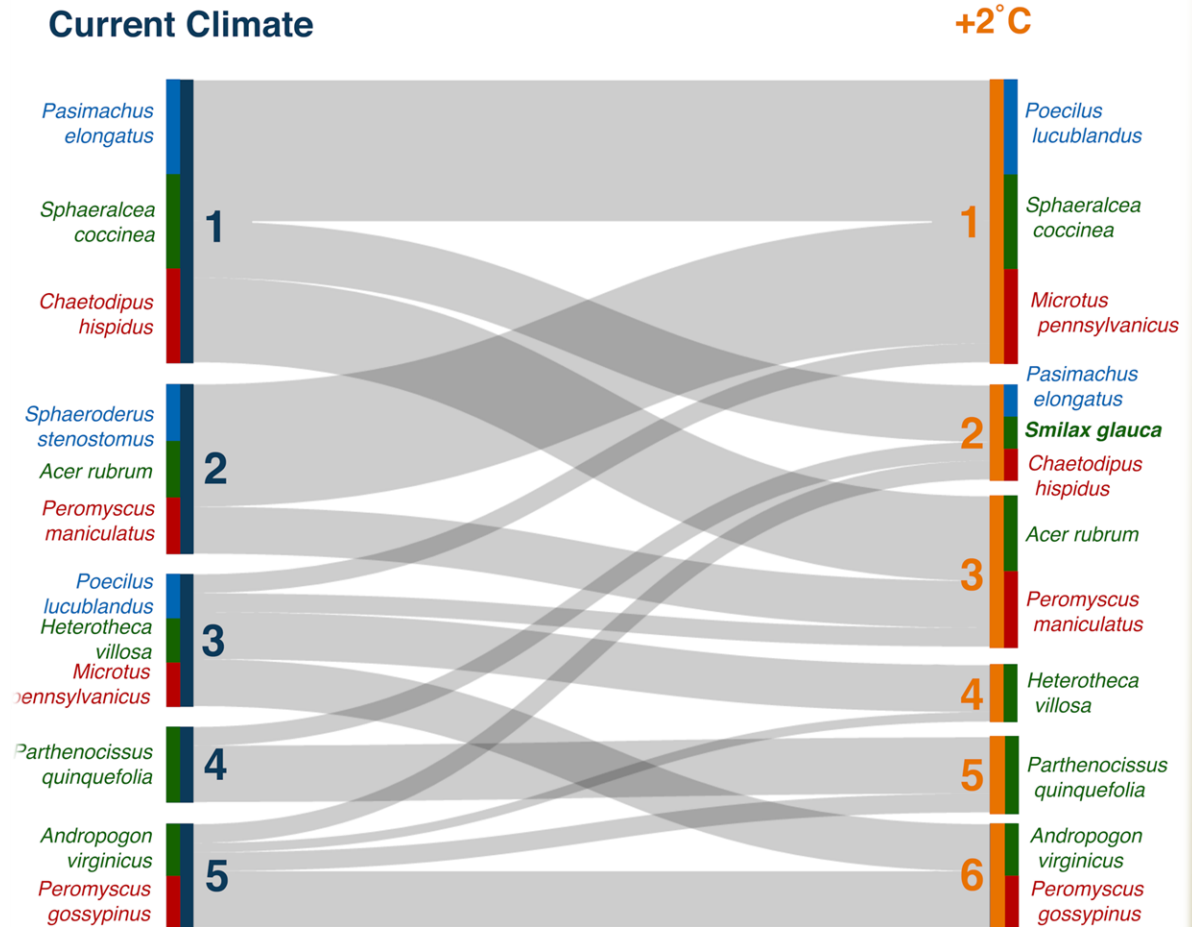
- Current climate





+2°C: Community reorganization

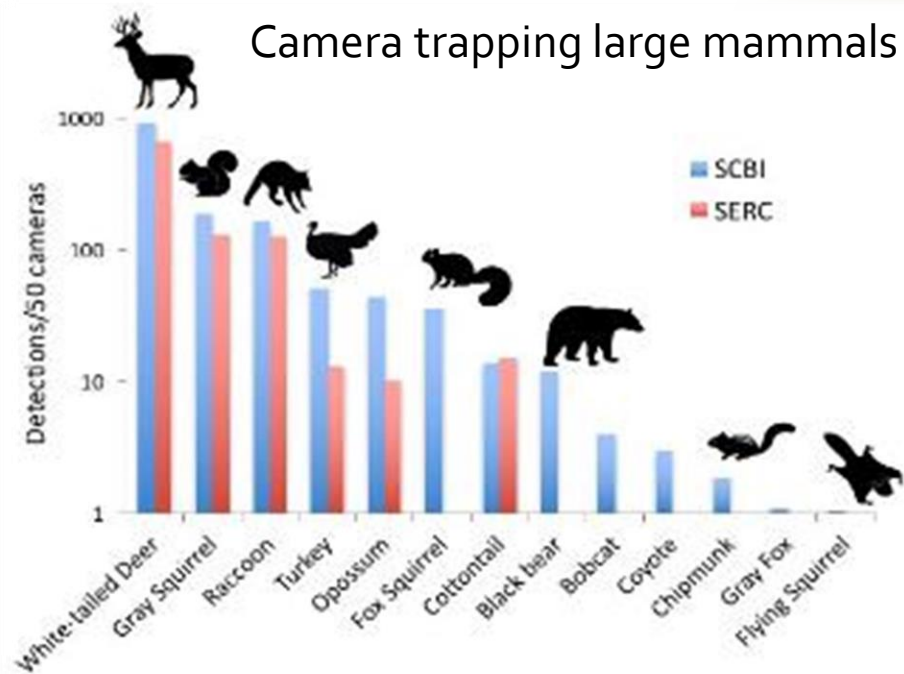
- Change mean and variance of all climate variables, mediated by habitat





The missing component: food

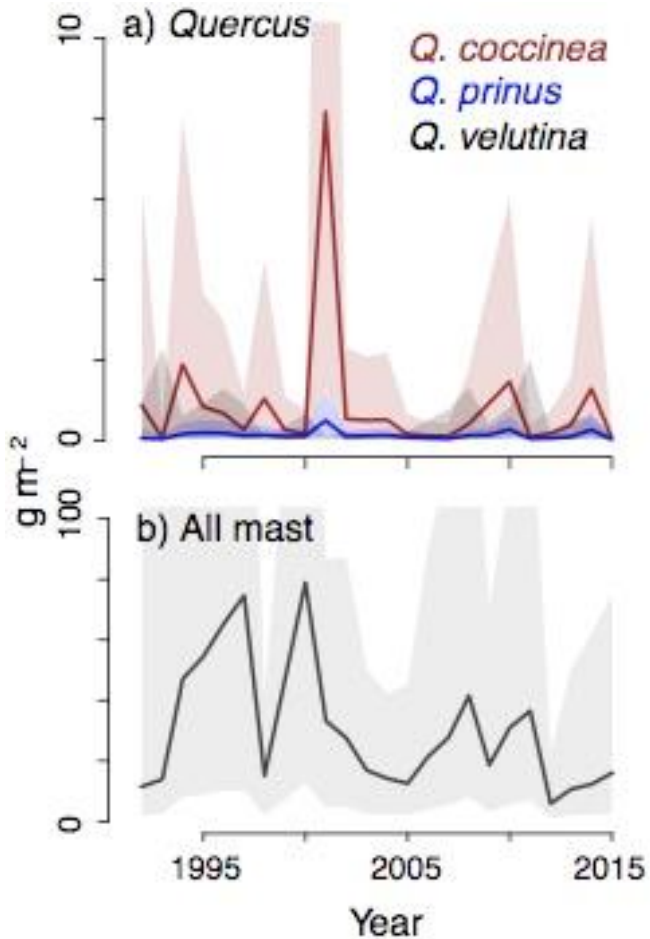
- Biodiversity predictions emphasize climate/edaphic
- Challenge:
 - Mean benefit/variance cost
 - Scale-dependence: each consumer in its own way



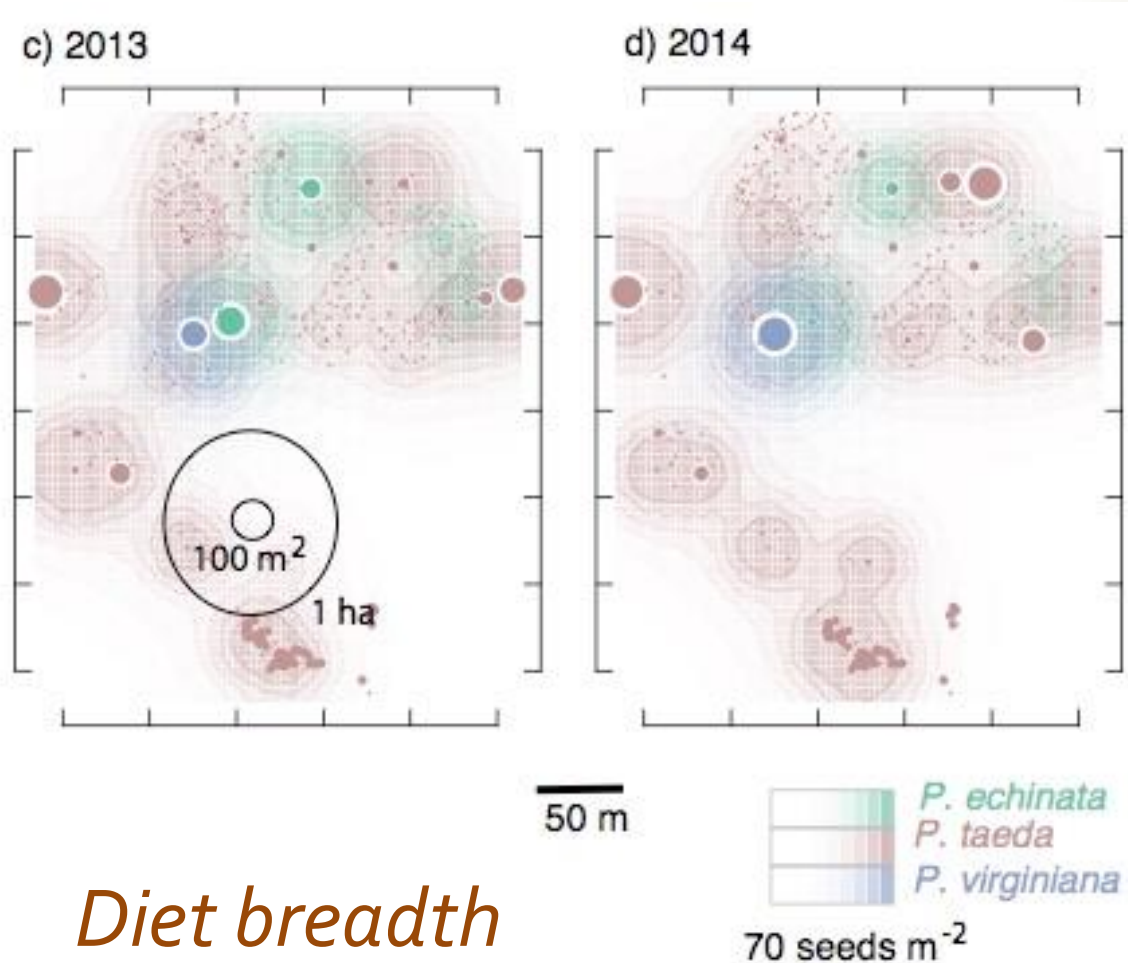


Scale-dependent variance in resources

In time



In space

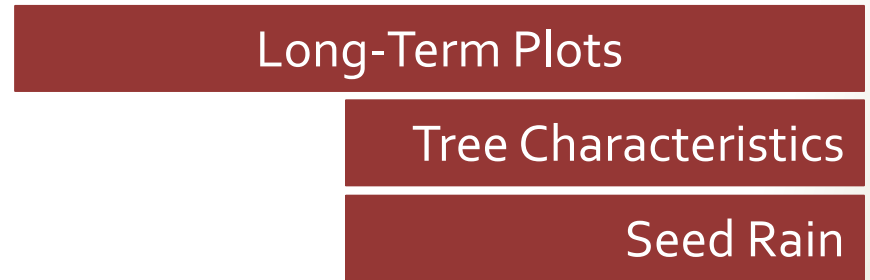
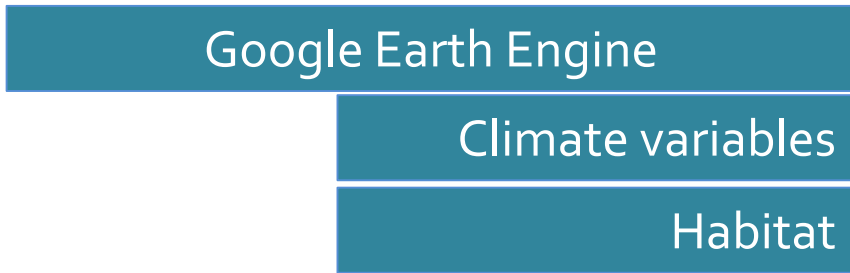


Diet breadth



NSF-funded MASTIF: Mast inference and forecasting

Mean benefit vs. variance cost of resources: scale-dependence, diet breadth



Source detection: fecundity of each tree:

$$\text{Seed Rain} = \text{Effort} \times \text{Fecundity} \times \text{Dispersal}$$

Habitat-specific mean vs variance at all scales:

$$\text{Resource Score} = \text{Mean Seed Rain} \times \text{Nutritional Quality} / \text{Variance}$$




MASTIF: translate individual fecundity to habitat resource value

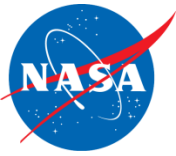
$$\text{Resource Score} = \text{Mean Seed Rain} \times \text{Nutritional Quality} / \text{Variance}$$

- Nutritional database of consumer, site-specific resource scores
- Use estimates of fecundity and dispersal to expand inference to FIA



Efficient to add new datasets

- **Biodiversity data**
 - NEON: bird counts, pathogen status of ticks, mammals
 - NSF funding: mast availability and large vertebrates
 - FIA
 - eBird/BBS
 - Scripts/tutorials on GitHub/CRAN for user data
- **Environmental, habitat, remote sensing**
 - Incorporating Lidar from NEON
 - Integrating additional datasets with GEE
 - Download/pre-process from NASA's DAACs for remote sensing data not available on GEE

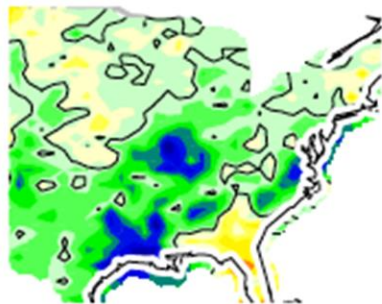


Web-based predictions

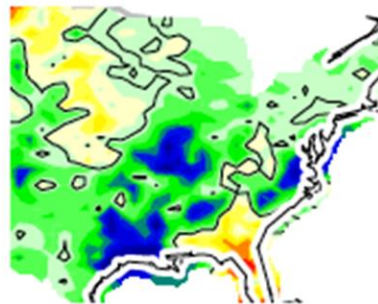
<http://www.pbgjam.org/>

- Location-based
- Species or species group
- Question-driven
- Explanation-the important variables contributing to change

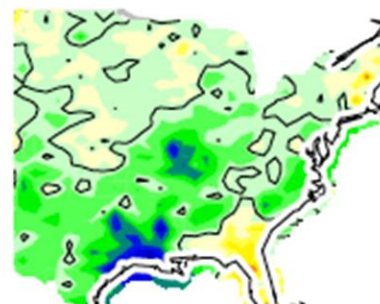
C) Richness change (% losses per 5 yr)



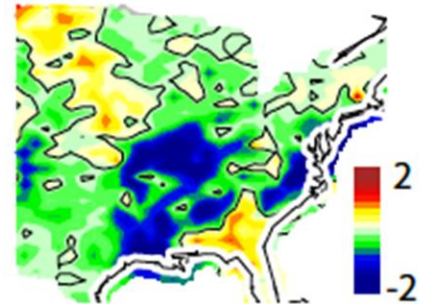
All species



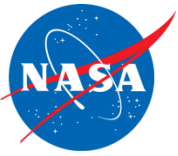
Ground beetles



Plants



Small mammals

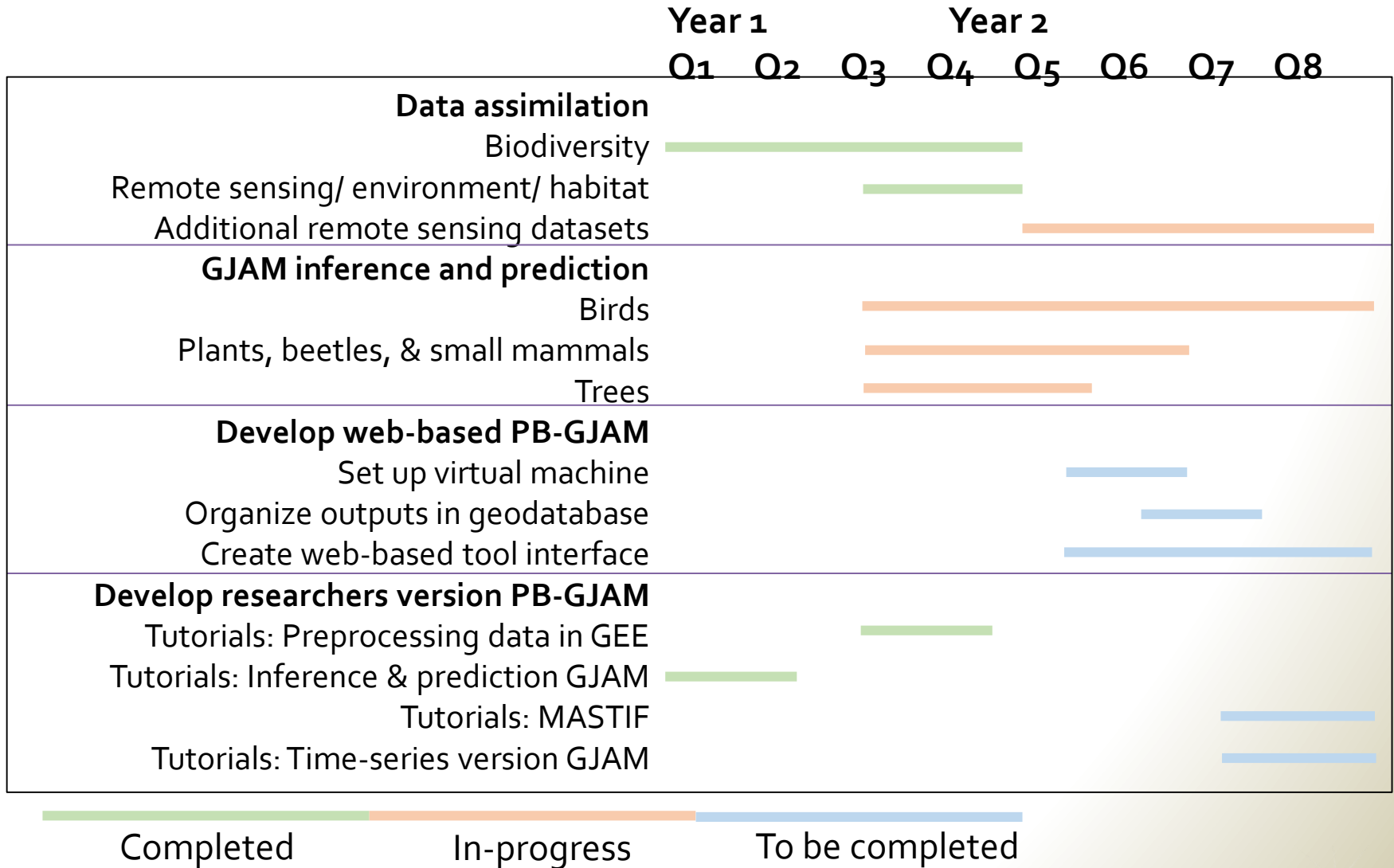


Fully open-source, algorithm documentation

- Fully open-source on CRAN
- Distribution theory in primary literature
- Algorithm documentation Rmarkdown vignettes, R help pages
- GJAM on cran: <http://rpubs.com/jimclark/234762>
 - Installed > 16,000 times
- MASTIF built, ready for cran: <http://rpubs.com/jimclark/281413>



Project Schedule



Completed

In-progress

To be completed



Additional info

- Bachelot B., Uriarte M., Muscarella R., Forero-Montana J., Thompson J., McGuire K., Zimmerman J.K., Swenson N.G. and J.S. Clark. 2018. *Associations among arbuscular mycorrhizal fungi and seedlings are predicted to change with tree successional status*. **Ecology**.
- Clark. J.S. 2016. *Why species tell us more about traits than traits tell us about species: predictive analysis*. **Ecology**.
- Clark. J.S. 2016. **gjam: Generalized Joint Attribute Modeling**, <https://cran.r-project.org/web/packages/gjam/index.html>
- Clark, J.S., D. Nemergut, B. Seyednasrollah, P. Turner, and S. Zhang. 2017. *Generalized joint attribute modeling for biodiversity analysis: Median-zero, multivariate, multifarious data*. **Ecological Monographs**.
- Taylor-Rodriquez, D., Kaufeld, K.A., E. M. Schliep, J.S. Clark, and A.E. Gelfand. 2017. *Joint species distribution modeling: dimension reduction using Dirichlet processes*. **Bayesian Analysis**.