



Region-wide calibration of 3-PG using data assimilation

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Many others from the 3PG team (especially Evan, Carlos, and Randy)

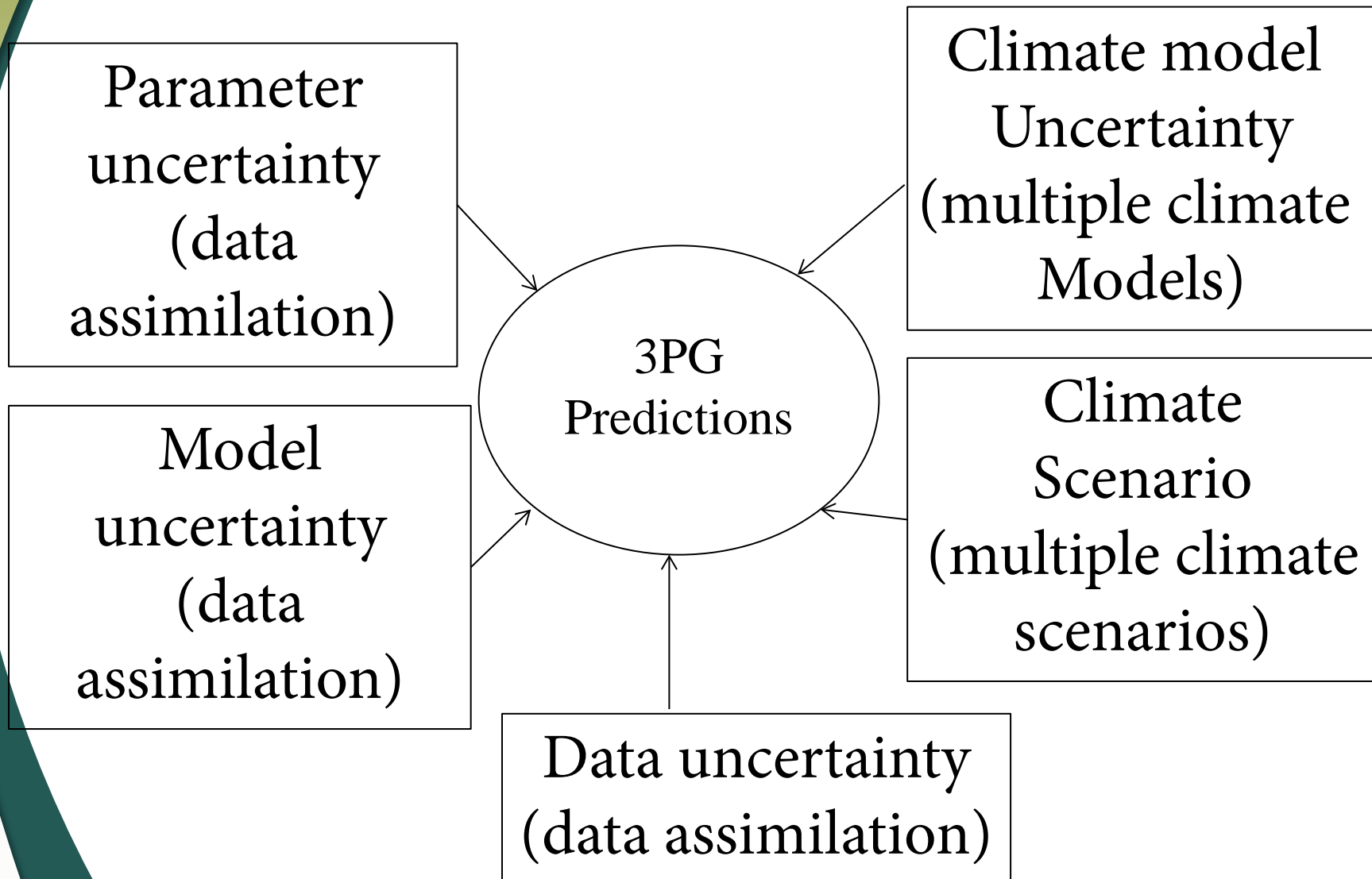


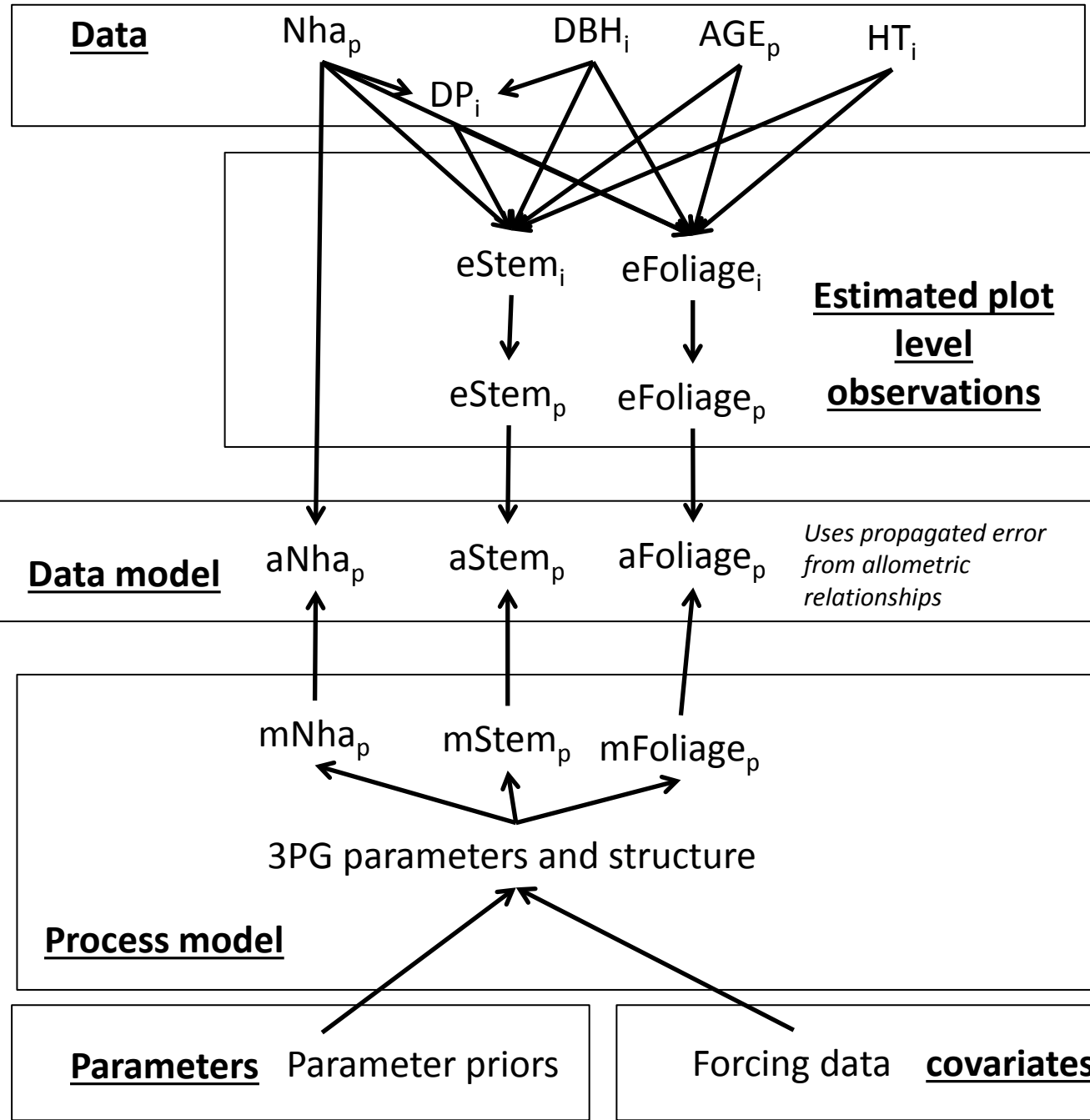
Overview

Make predictions for loblolly pine productivity with a known uncertainty that is consistent with region-wide data and prior knowledge



Known Unknowns





Tier 1/Tier 2
data assimilation



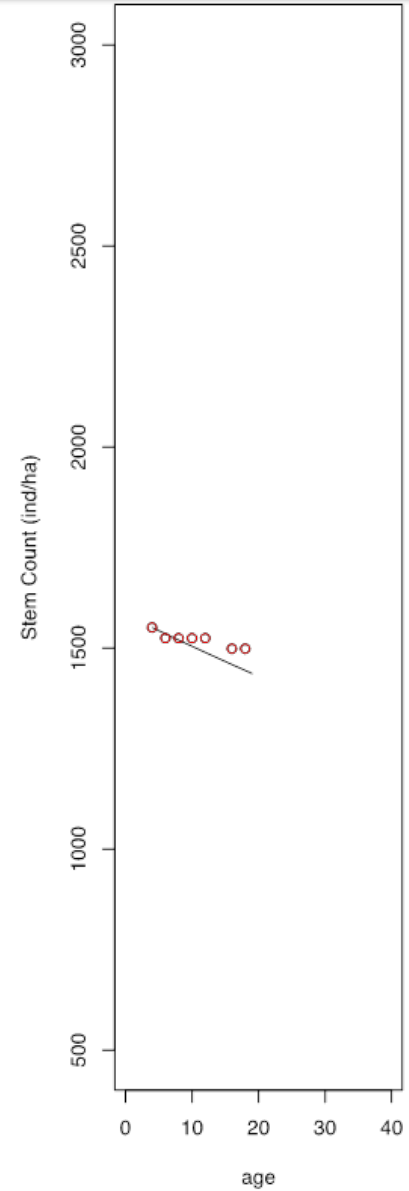
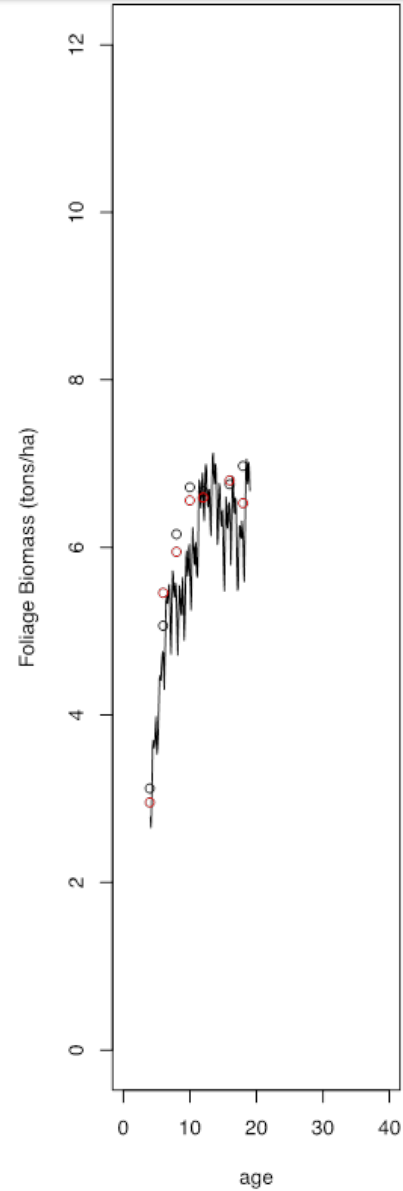
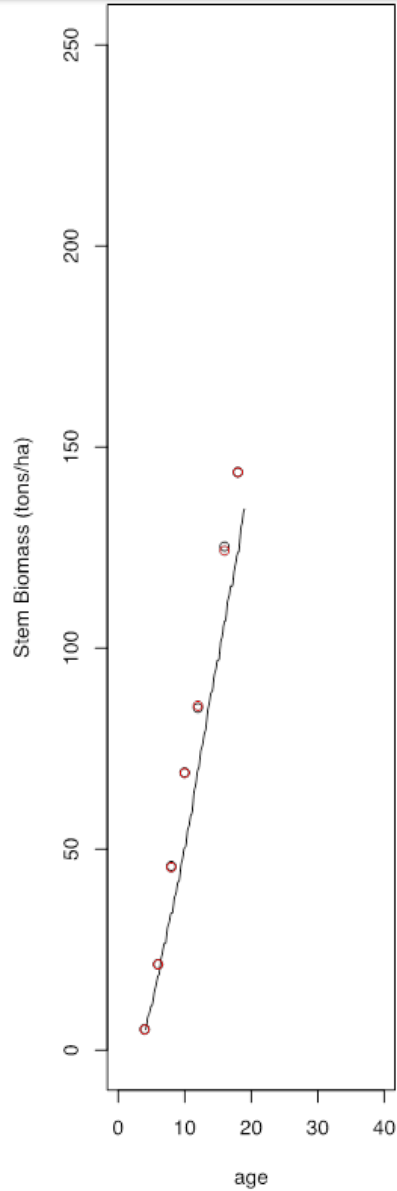
Completed

- Data-assimilation algorithm is running on 44 sites from Carlos set of validation data using the Flavor C.
- ~88 sites are not used in data-assimilation and are available for testing.
- Our algorithm now allows for
 - ‘data uncertainty’ associated with using allometric equations to calculate plot level biomass values
 - Estimating initial available soil water
- Capacity to make single plot predictions that integrate over parameter uncertainty
- Capacity to simulate multiple climate models and scenarios at the plot level



Preview

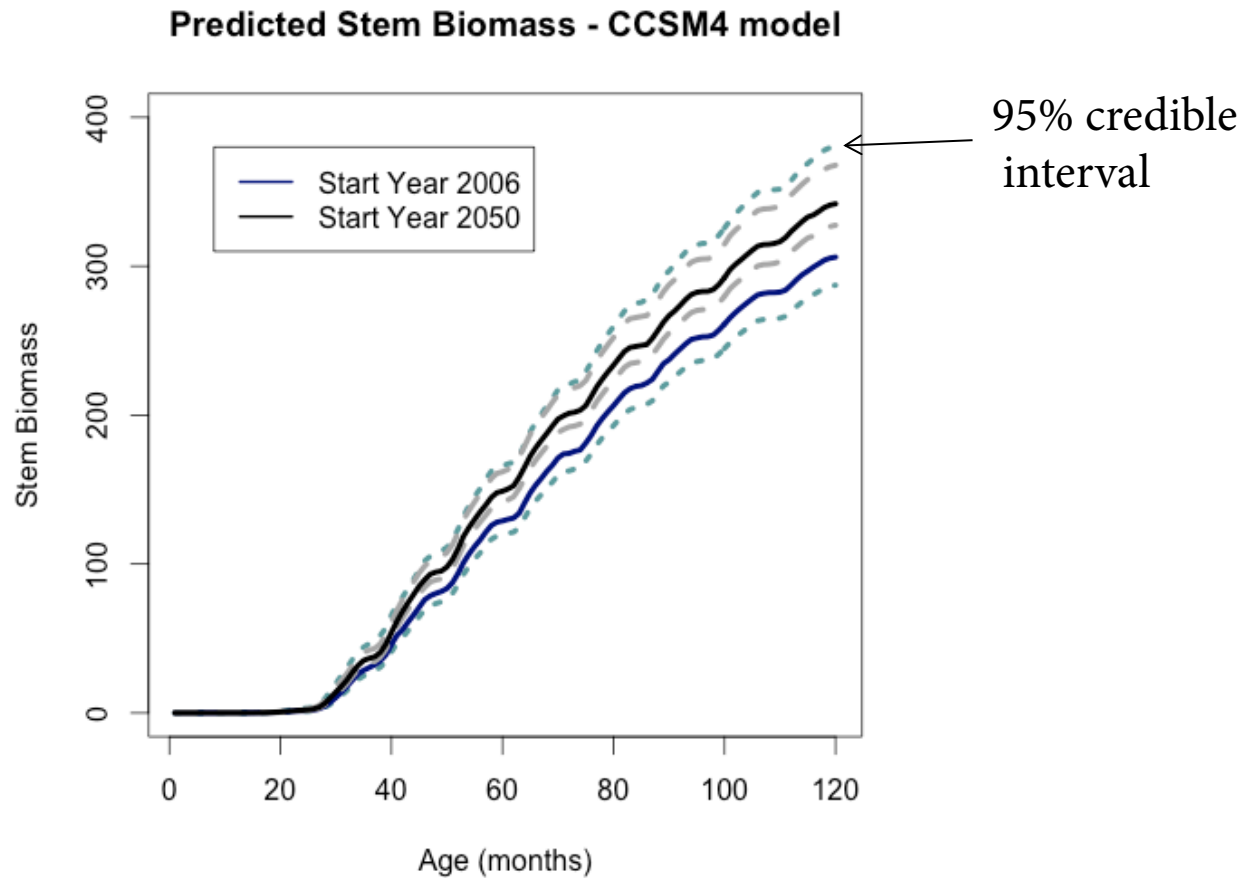
plot number = 19





Preview

- Example test analysis from unfinished simulation





Current status

- Working with Eric (AIM 1) to organize the Tier 3 and Duke FACE.
 - Starting with simulating the control and drought treatment at the Virginia site Tier 3
 - Focus on biomass, LAI, litterfall, and canopy transpiration
 - Simulating Duke ambient and elevated CO₂ treatments
 - Focus on biomass, LAI, litterfall, and canopy transpiration
- Working with Eric and Asko (AIM 1) to organize Duke and Coastal NC flux tower and biomass data
 - Focus on winter time GPP and canopy transpiration
 - Winter allows the removal of deciduous tree influence



Current Status

- The integration of both observational and experimental data from across the region is unique
 - Drought response and elevated CO₂ responses will be included in the parameterization
- Trade-off among parameters means that we need to fix or highly constrain parameters.
 - Example: multiple ways to fit a reduction in foliage biomass (or LAI) with age
 - Example: Minimum temperature and frost day parameters



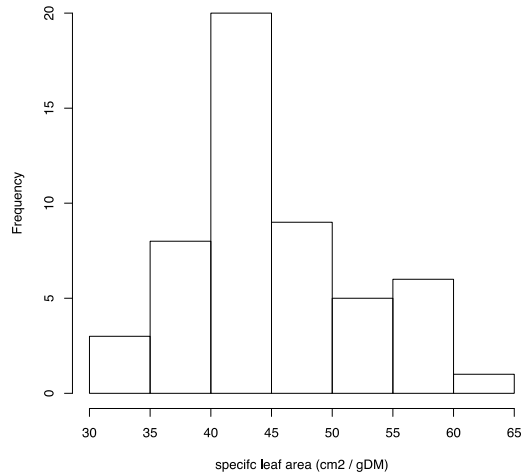
Needs

- Priors
 - Specific leaf area
 - Leaf-life span
 - Strength of photosynthesis decline with age
 - Max and min monthly temperatures for photosynthesis
 - Root allocation or aboveground to belowground biomass ratios
 - Ratio of foliage to leaf allocation at 2 and 20 cm DBH
- What would be a good method to create the priors?
 - Sharing excel files with observations
 - Group call with interested parties

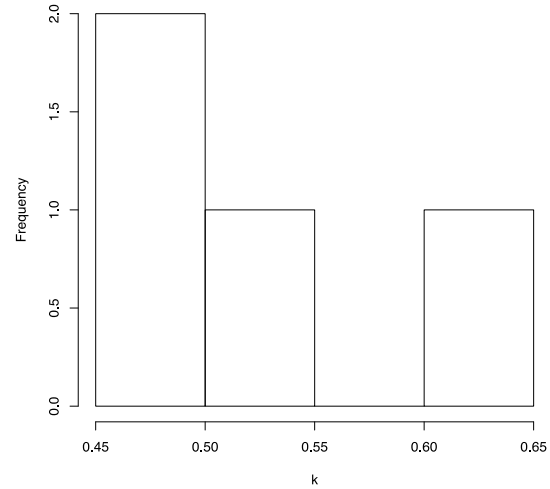


Examples of priors (but need more data)

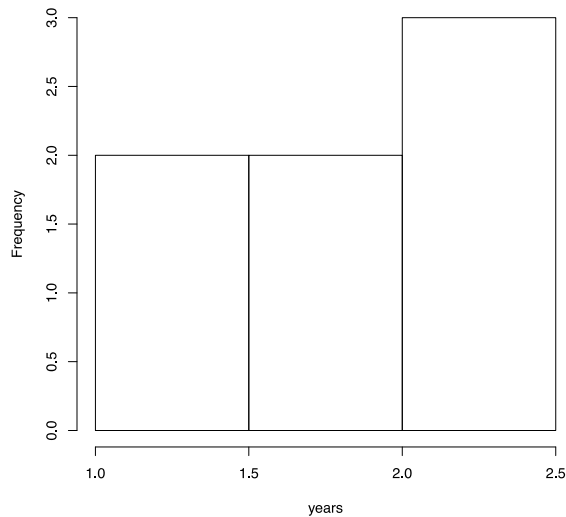
specific leaf area prior (n=52)



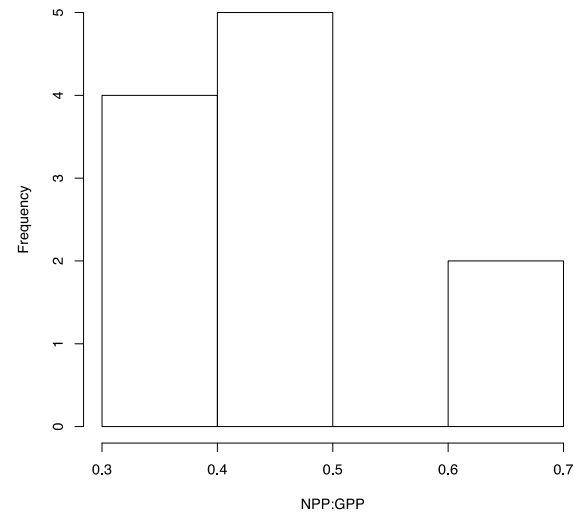
light extinction coefficient (n=4)



leaf life span (n=7)



NPP:GPP (n = 11)





Other needs

- Idaho 'observed' climate data to simulate sites where weather data is not available



Upcoming

- Three AGU oral talks in the session:
 - Constraining Ecosystem Carbon Uptake and Long-Term Storage with Integrated Modeling, Experiment, and Observation



Approaches and Constraints

Site Index Expansion



Site Index

$$SI = f(\textit{Soil}, \textit{Climate}, \textit{Silviculture})$$

- We are already varying climate and silviculture within PINEMAP
 - Thus, we would prefer a SI map which filters out these influences on SI
- Immediately, we have the question of whether or not estimating an extended SI for loblolly pine is within the scope of the original grant

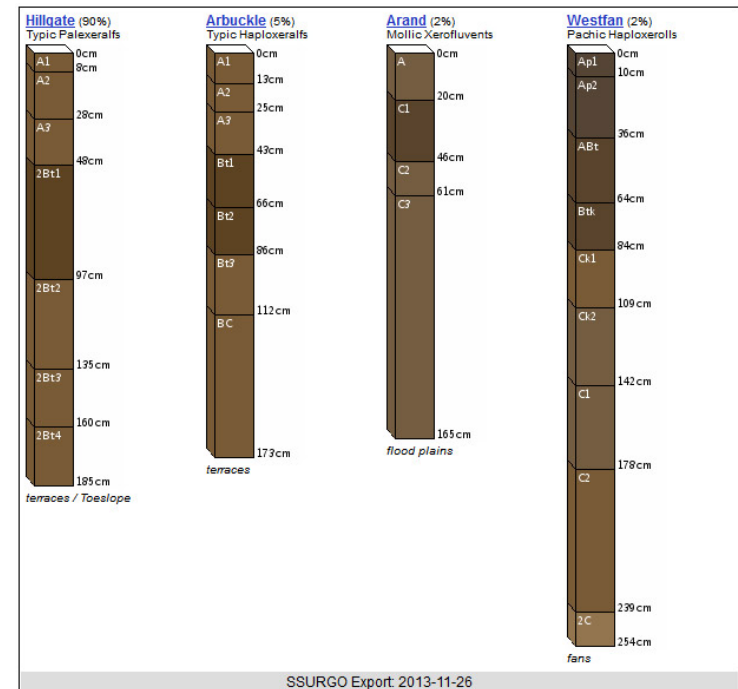


SSURGO

- The SSURGO database contains data across the CONUS
 - Broken down into geographic “mapunits” which are in turn comprised of “components” which represent a specific sequence of “horizon” data



http://www.arcsie.com/internal_img/VectorizationFig_Final.jpg



<http://casoilresource.lawr.ucdavis.edu/software/postgis-spatially-enabled-relational-database-sytem/analysis-ssurgo-data-postgis-overview/logistics-getting-connected-and-executing-queries/getting-parent-material-data-out-ssurgo/>



SSURGO

- The SSURGO dataset includes a table (coforprod) which lists SI measurements by component for species observed in a particular component
 - The values for loblolly pine were used as the basis for previous SI maps for regional 3-PG runs
 - Missing values were backfilled using a state-by-state approach in which the missing value was imputed by the mean known SI for that particular component's series
- However, if we want to extend the SI map beyond places where loblolly pine data are observed, we need a different approach



Two Methods

Method	Advantages	Disadvantages
SI matching to other species with different ranges	<ul style="list-style-type: none">• Uses observed data• Straightforward processing	<ul style="list-style-type: none">• Restricted by ranges and data availability for other species• Climate implicitly included• Doesn't actually impute "missing" components
Modeling SI using edaphic factors only (possibly based on "standard" climate inputs)	<ul style="list-style-type: none">• Data readily available• No restrictions on range	<ul style="list-style-type: none">• Generally weak fits• Confounding influences on "soil" variables

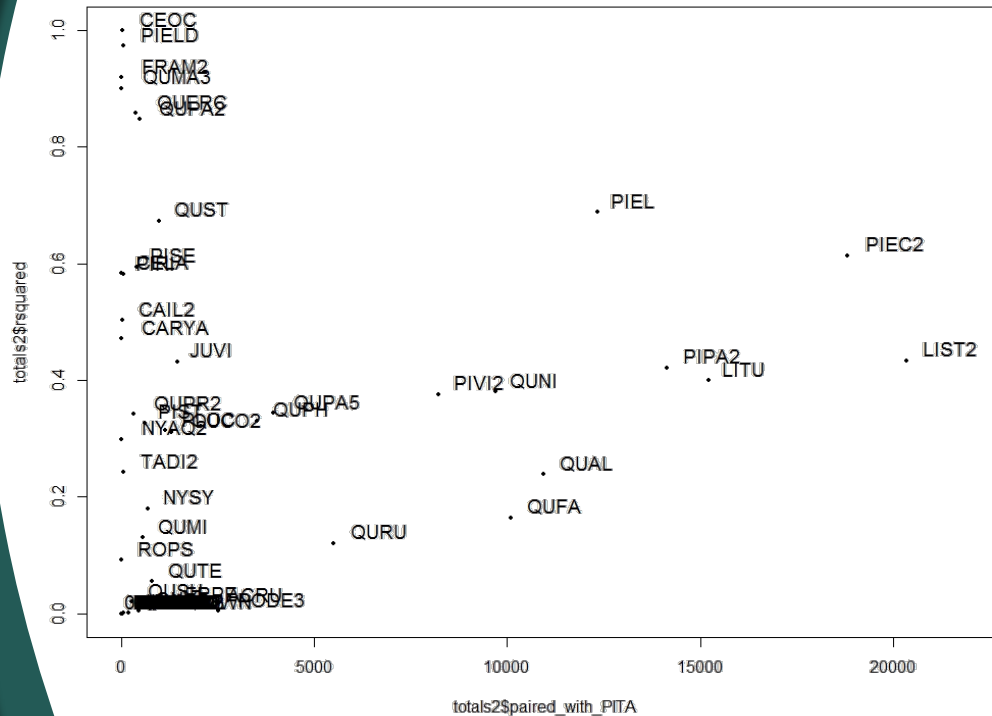


SI Matching to Other Species

- From the coforprod table for entire region of interest, convert from long to wide format
 - Each row represents a single component, with columns for the SI of each species (~150 species in all)
- For each candidate species, count the number of components which have data for that species *and* loblolly pine
 - Also generate a simple linear regression between the SIs for that species against loblolly pine



SI Matching to Other Species



By the numbers, the best candidates include...

- Shortleaf Pine (PIEC2)
- Sweetgum (LIST2)
- Slash Pine (PIEL)
- Yellow Poplar (LITU)
- Longleaf Pine (PIPA2)

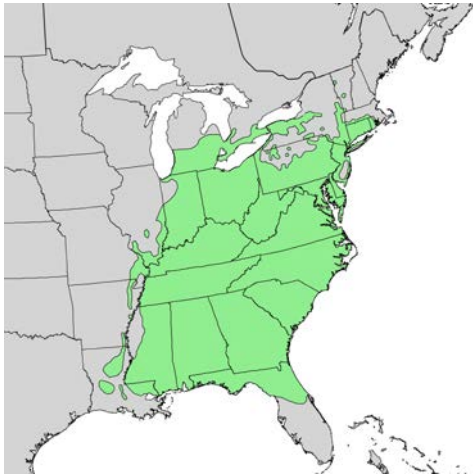
Other contenders might be...

- White Oak (QUAL)
- Water Oak (QUNI)
- Virginia Pine (PIVI2)

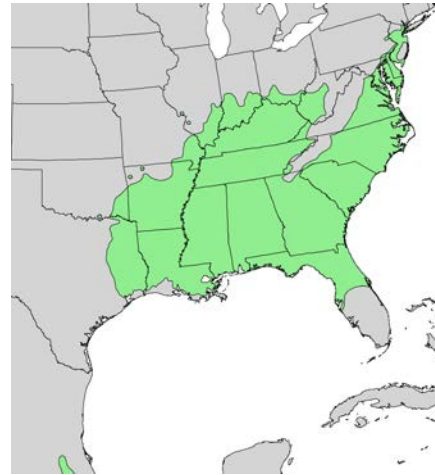


SI Matching to Other Species

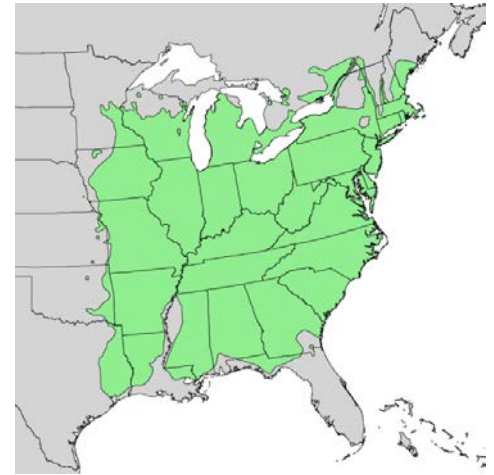
- Species with range that may be suitable for SI expansion



Yellow Poplar (LITU)
 $R^2 \sim 40\%$



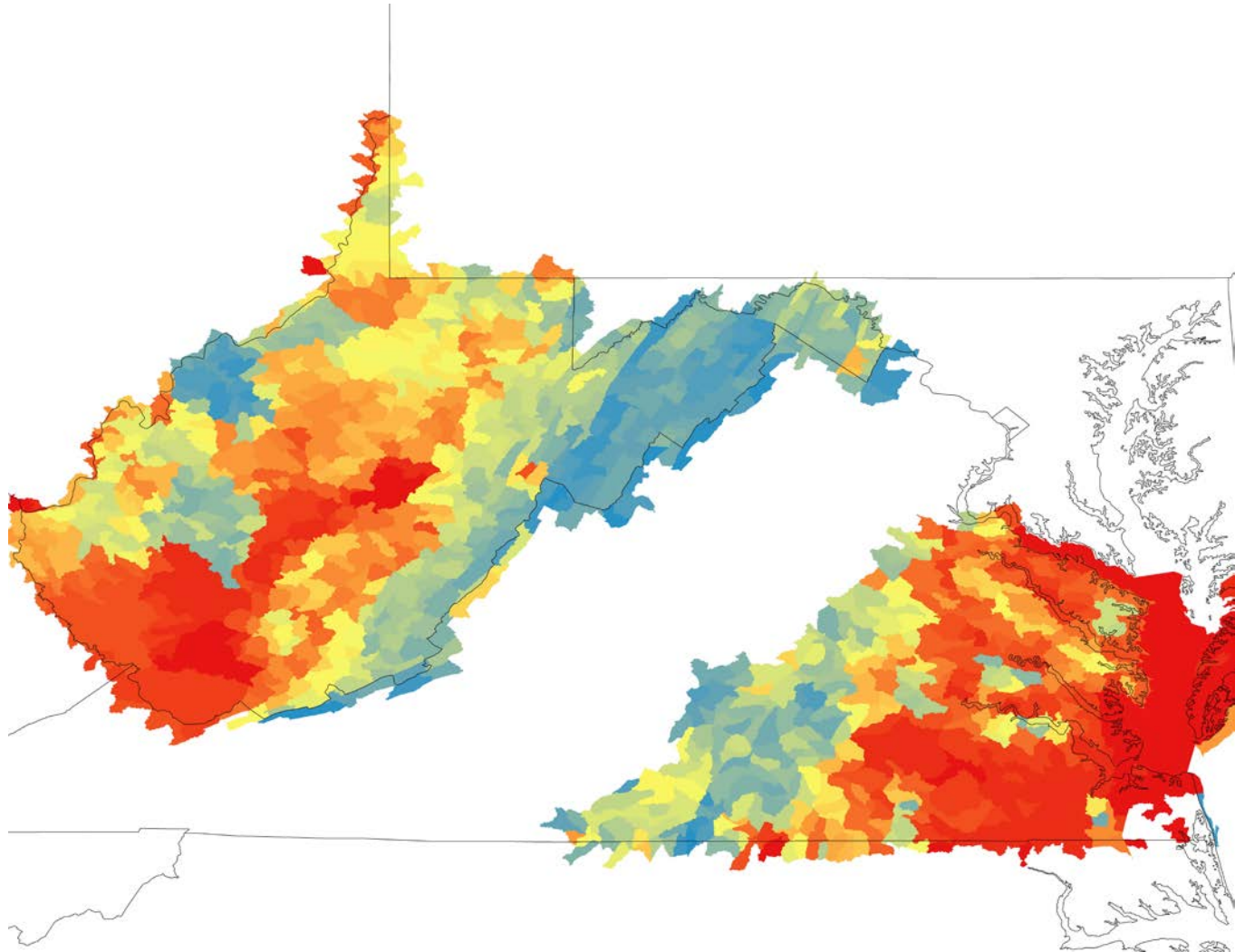
Sweetgum (LIST2)
 $R^2 \sim 43\%$



White Oak (QUAL)
 $R^2 \sim 24\%$



SI Matching to Other Species





Edaphic SI Modeling

- The greatest challenge in modeling SI by soil alone is that SI is intrinsically linked to climate as well
 - Need to be wary of confounding variables
 - Perhaps model SI with the climate inputs included, then use a typical or standardized set of climate inputs to get the variation due to soil



Edaphic SI Modeling

- Variables available at the component and horizon levels

Variable	Type	Table	r_{SI}
Clay	Soil	Chorizon	-0.25
Silt	Soil	Chorizon	0.11
Organic Material	Soil	Chorizon	0.11
Slope	Geographic	Component	-0.41
Elevation	Geographic	Component	-0.33
Aspect	Geographic	Component	0.09
Albedo (dry)	Soil	Component	-0.12
Air Temperature (Annual Mean)	Climate	Component	-0.11
Precipitation (Annual Mean)	Climate	Component	-0.11
Frost Free Days	Climate	Component	-0.08
Available Cations	Soil	Chorizon	-0.12



Edaphic SI Modeling

- Nonlinear model form akin to Charles Sabatia's SI function (for the G&Y model) seems desirable, but unfortunately even the initial parameter values for model fitting have been extremely difficult to estimate
 - The following results are from using a linear model



Edaphic SI Modeling

Residuals:

Min	1Q	Median	3Q	Max
-56.710	-5.094	0.447	5.516	34.243

Residuals:

Min	1Q	Median	3Q	Max
-55.368	-4.885	0.772	4.902	33.269

(Intercept)

clay

silt

om

cec7

airtemp

ffd_r

map_r

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.53 on 50989 degrees of freedom

(90271 observations deleted due to missingness)

Multiple R-squared: 0.2566, Adjusted R-squared: 0.2565

F-statistic: 2933 on 6 and 50989 DF, p-value: < 2.2e-16

Coefficients:

(Intercept)

clay

silt

om

cec7

airtemp

ffd_r

map_r

slope_r

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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Multiple R-squared: 0.2566, Adjusted R-squared: 0.2565

F-statistic: 2933 on 6 and 50989 DF, p-value: < 2.2e-16

Residuals:

Min	1Q	Median	3Q	Max
-54.638	-4.682	0.563	4.527	30.706

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	88.7193336	0.1115566	795.285	< 2e-16 ***
clay	-0.1054642	0.0026671	-39.542	< 2e-16 ***
silt	0.0838367	0.0019434	43.139	< 2e-16 ***
om	0.2832498	0.0324898	8.718	< 2e-16 ***
slope_r	-0.3789771	0.0049274	-76.912	< 2e-16 ***
elev_r	-0.0146422	0.0003069	-47.710	< 2e-16 ***
aspectrep	0.0017459	0.0004314	4.047	5.19e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.53 on 50989 degrees of freedom

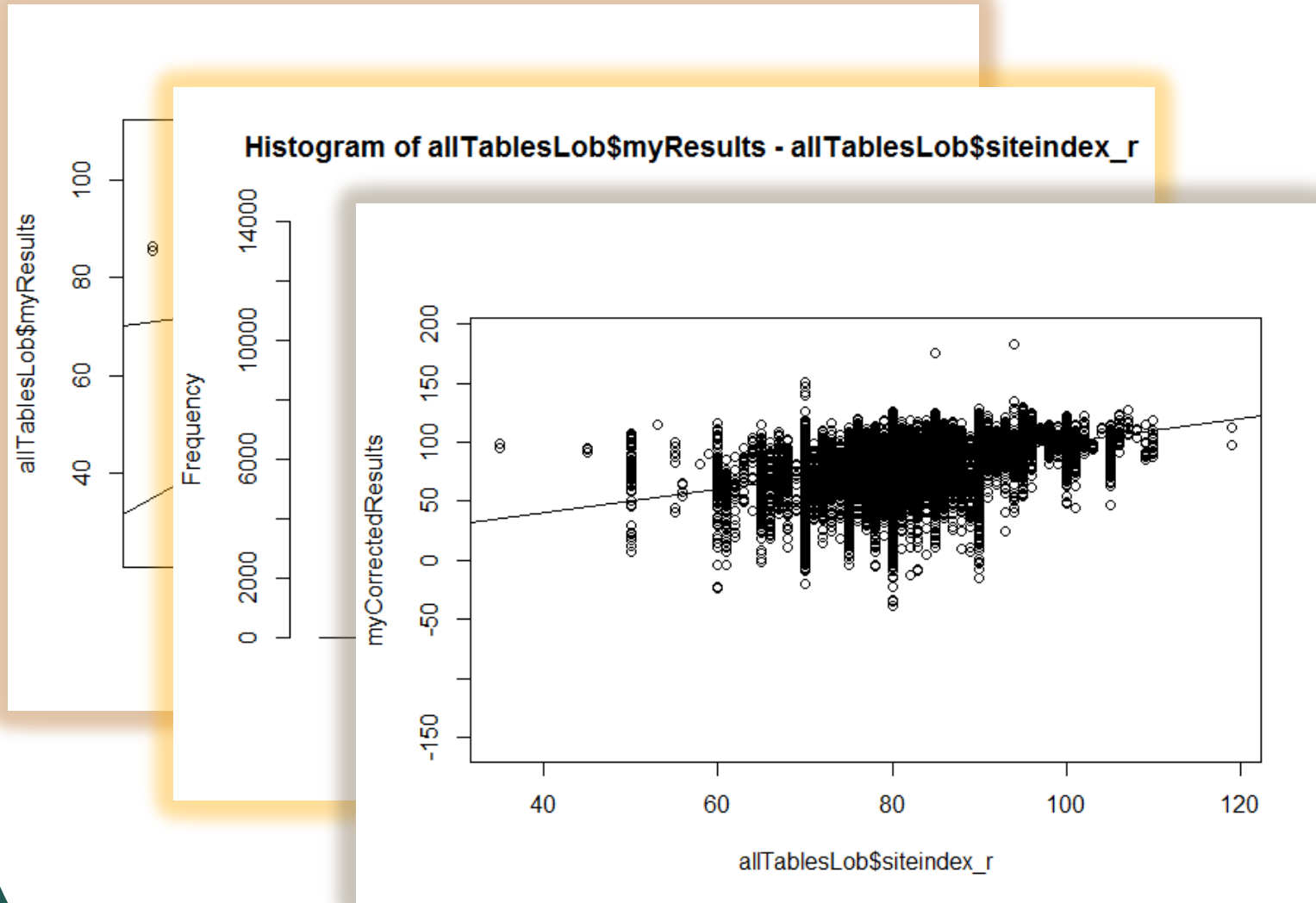
(65241 observations deleted due to missingness)

Multiple R-squared: 0.2566, Adjusted R-squared: 0.2565

F-statistic: 2933 on 6 and 50989 DF, p-value: < 2.2e-16



Edaphic SI Modeling





Conclusions and Questions

- Clearly, there are some major challenges and caveats to either approach to extending loblolly pine SI estimates beyond the natural range
- Questions:
 - Is it worth it?
 - Is it within the scope of PINEMAP?
 - If so, which approach should we use?
 - Yellow Poplar had the best match so far, but we still have numerous gaps to fill if we go this route