# Region-wide calibration of 3-PG using data assimilation

Team wide contributions

(individual contributions highlighted in presentation)

PINEMAP is a Coordinated Agricultural Project funded by the
USDA National Institute of Food and Agriculture, Award # 2011-68002-30185.

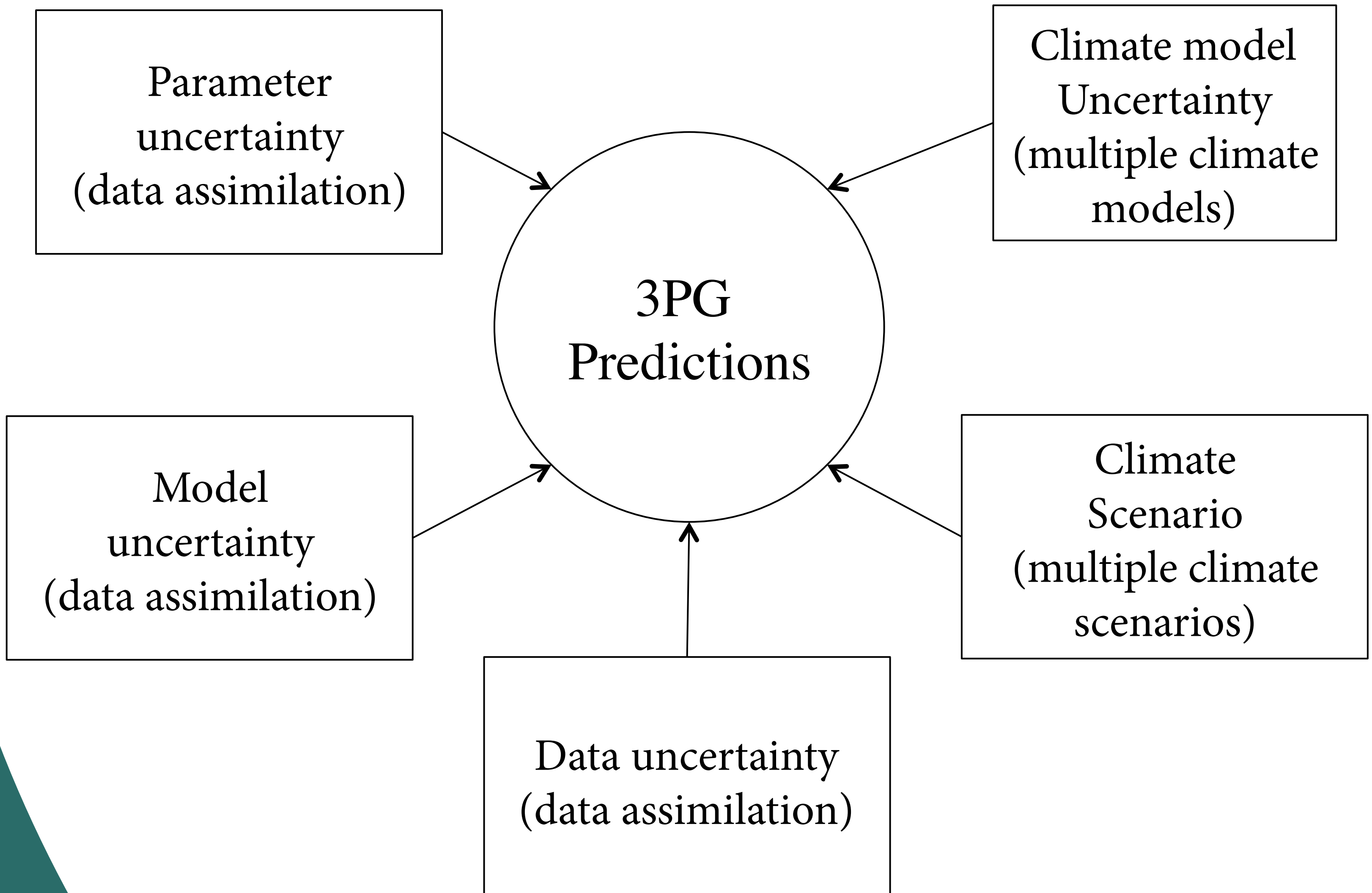
United States Department of Agriculture

National Institute of Food and Agriculture

# Overview

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

# Known Unknowns



PINEMAP

# Why data-assimilation?

TABLE 1. Distinguished characteristics of terms: forecasting, prediction, projection, and prognosis

| Term | Characteristics |
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| Forecasting | probabilistic statement on future states of an ecological system after data are assimilated into a model |
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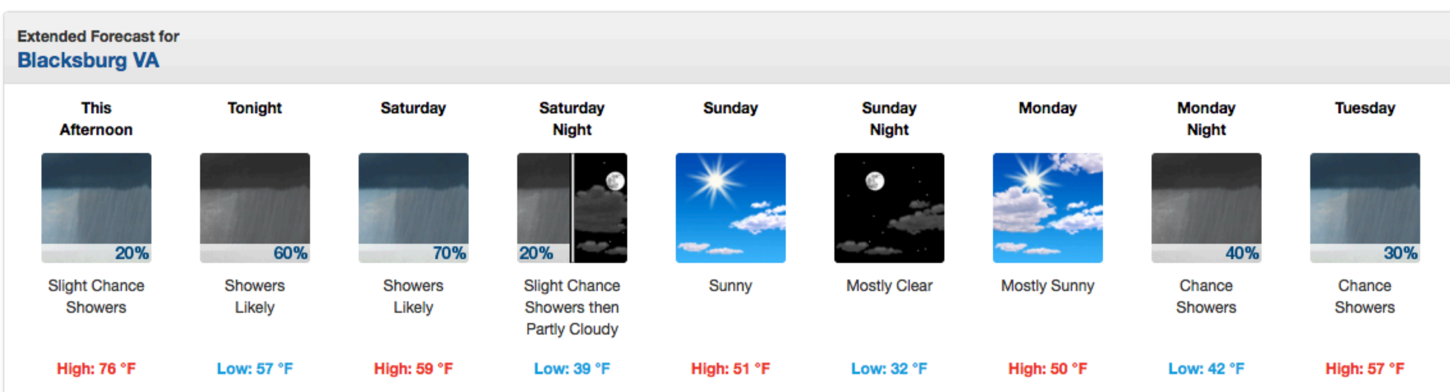
Move from predictions and projections to forecasting through the creation of probabilistic statements about the future growth




Luo et al 2011 *Ecological Applications*

# Why data-assimilation?

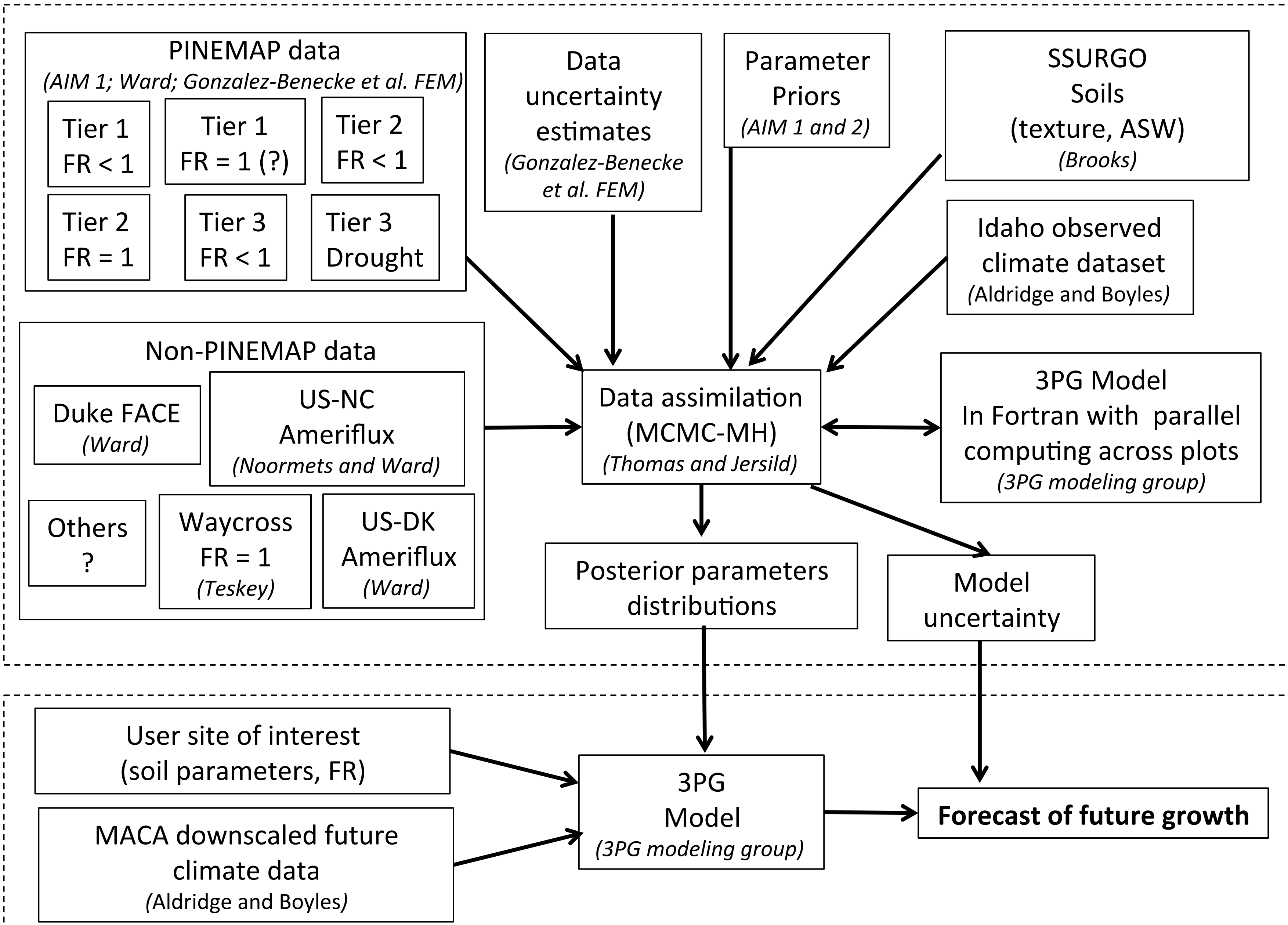
A data-assimilation system allows for automated re-calibration using alterative sets of plots or newly collected data

Easy to re-calibrate after model modifications or swapping of models

Accounts for uncertainty in parameters; we no longer need a single value

# Data Assimilation of PINEMAP Ecosystem Research (DAPER) System

Huge team effect!!!!



# PINEMAP Tier 1, 2, and 3 data

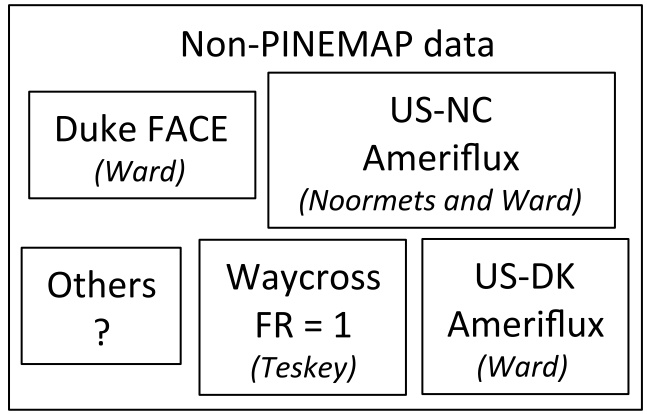
PINEMAP data

*(AIM 1; Gonzalez-Benecke et al. FEM)*

| | | |
|---|---|---|
| Tier 1<br>FR < 1 | Tier 1<br>FR = 1 (?) | Tier 2<br>FR < 1 |
| Tier 2<br>FR = 1 | Tier 3<br>FR < 1 | Tier 3<br>Drought |

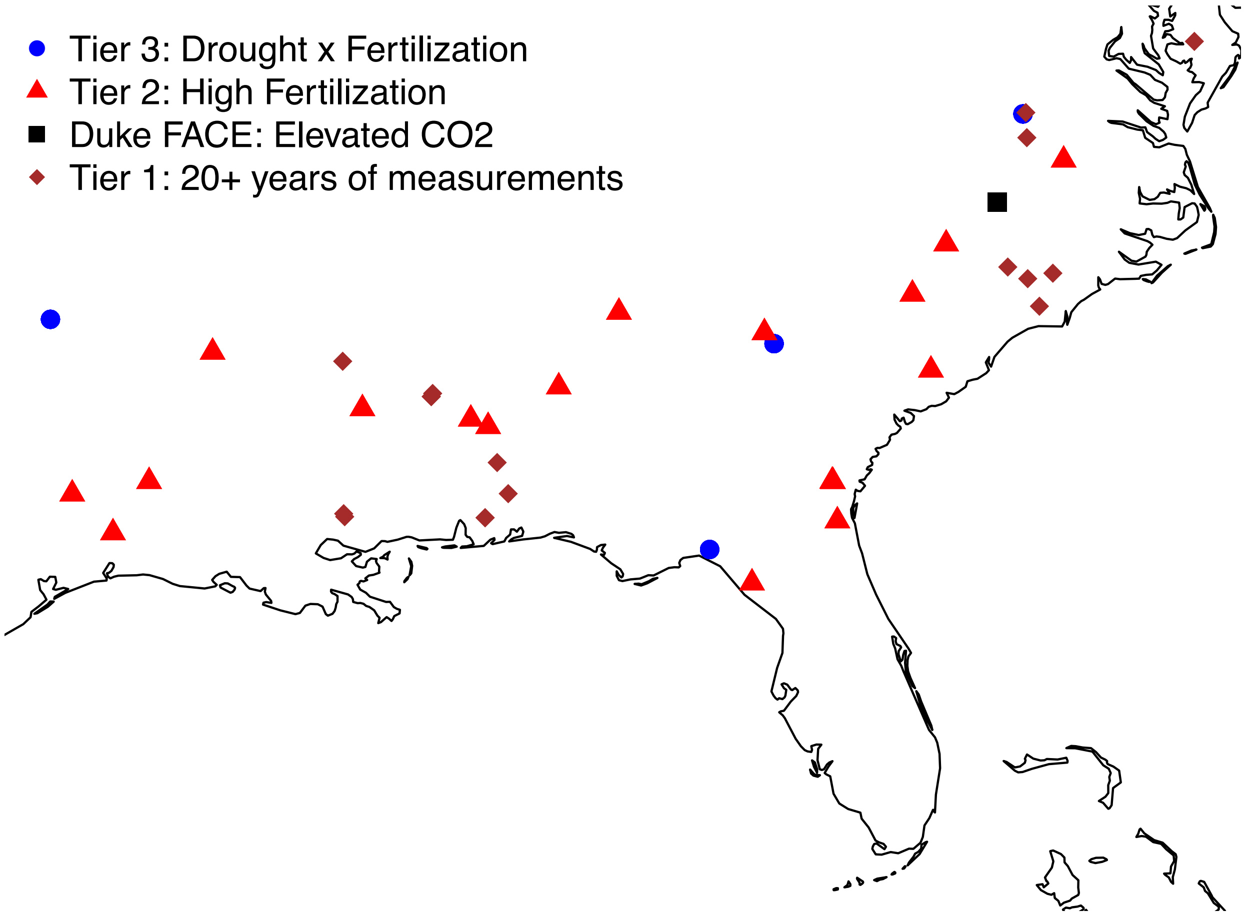
| Study | Objective for data-assimilation |
|---|---|
| Tier 1 FMRC Thinning (17 plots) | Large range of ages, includes plots with different atmospheric $CO_2$ (1980s – 2000s); region-wide climate gradients |
| Tier 2 FPC RW 18 (36 plots) | Paired plots with fertilization that allows FR = 1; region-wide climate gradients |
| Tier 3 (64 plots) | Constrain sensitivity to rain reduction and fertilization |
| Others? | Unique objective is important because of computational cost of adding plots |

# Non-PINEMAP data

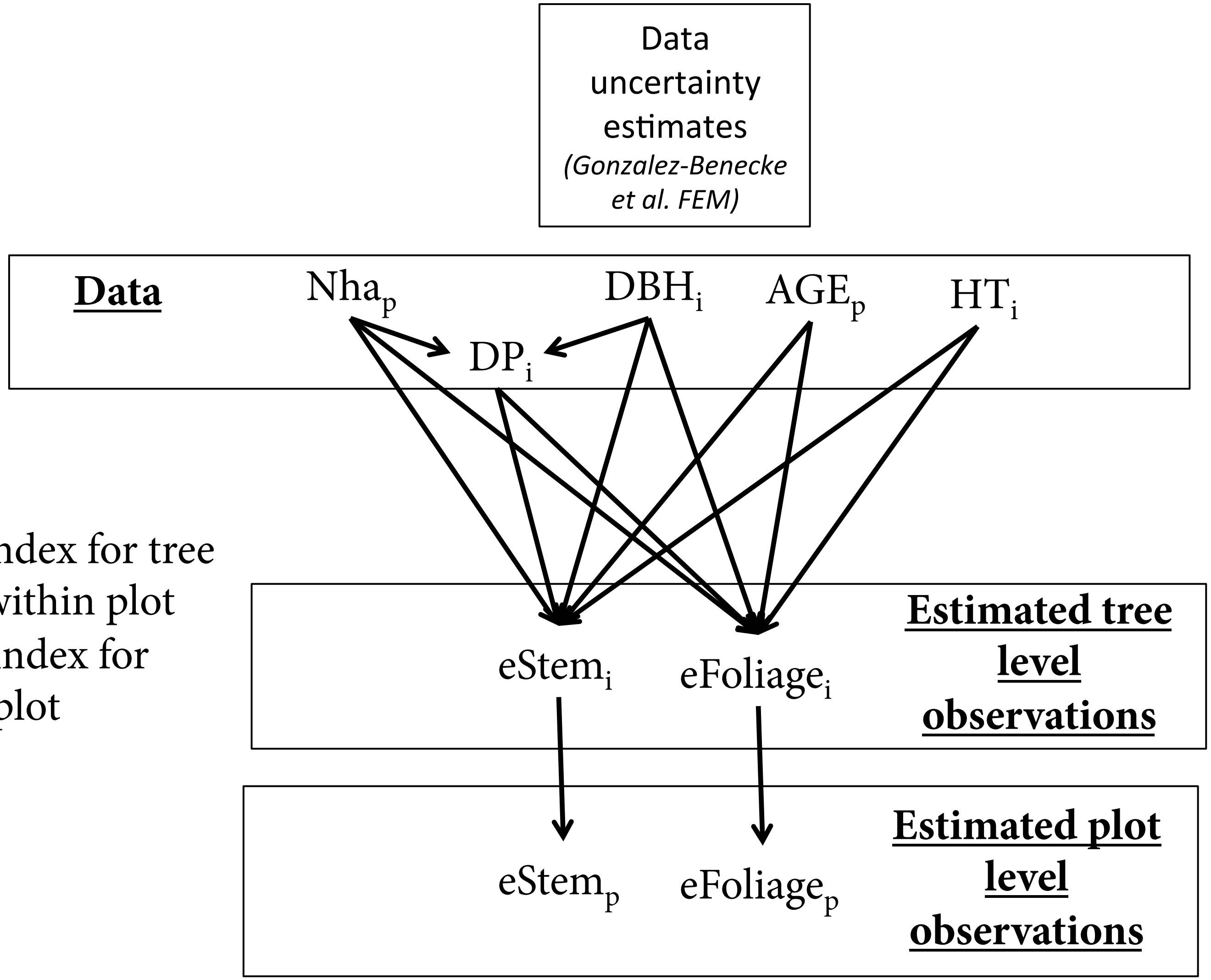



| Study | Objective for data-assimilation |
| --- | --- |
| Duke FACE (12 plots) | Elevated CO2; includes elevated CO2 and fertilization |
| Others | Can Ameriflux sites help constrain sensitivity to weather? |

# Region-wide coverage of data



# Tier 1, 2, and 3 estimations



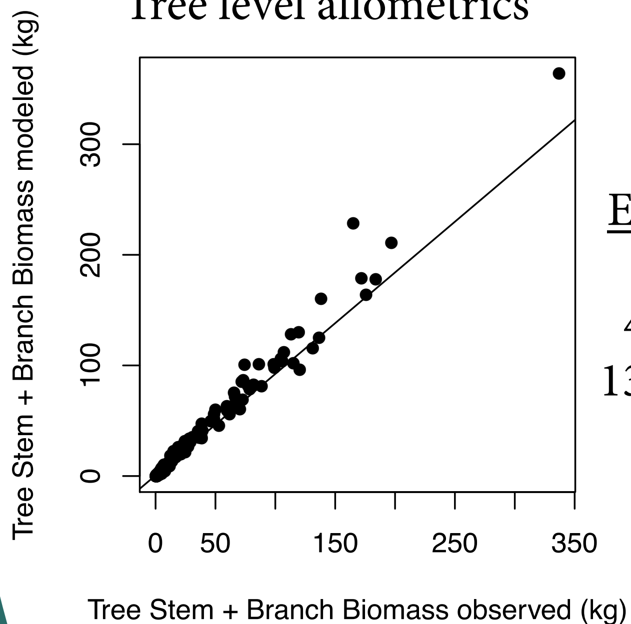

i = index for tree within plot

p = index for plot

# Accounting for observation uncertainty

Data uncertainty estimates *(Gonzalez-Benecke et al. FEM)*

Tree level allometrics

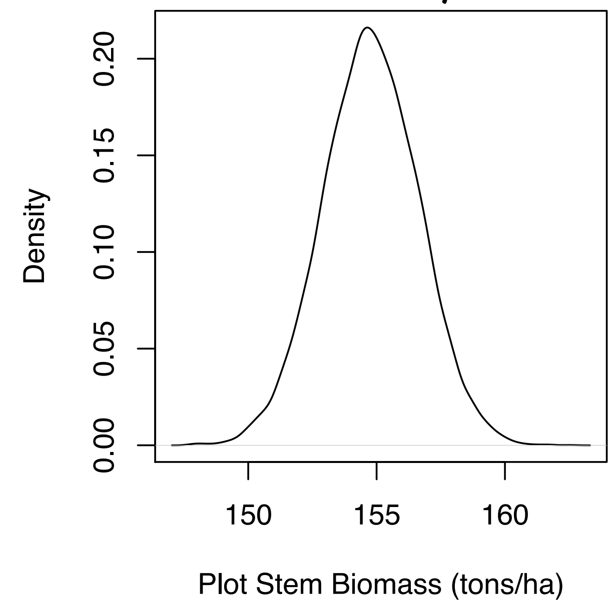



Standard deviation = $0.26M^{0.8}$
M = observed tree biomass
Variance is proportional to the mean

<u>Example plot information</u>
0.1 ha plot
41 individuals measured
136 tons stem biomass $ha^{-1}$

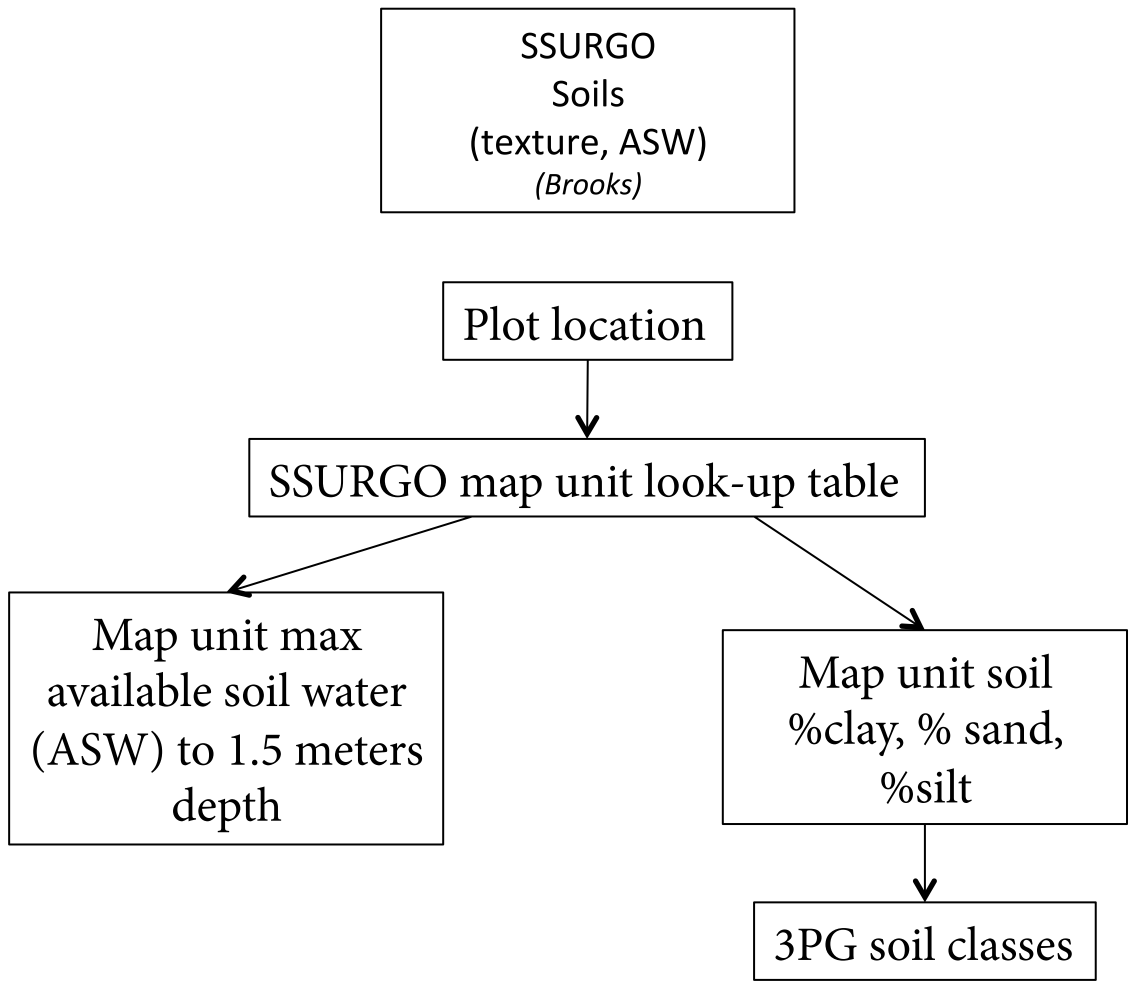
Bootstrap method to propagate

Plot specific observation uncertainty




**Allows for observational error to not be included in parameter and model error**

# Soil input database



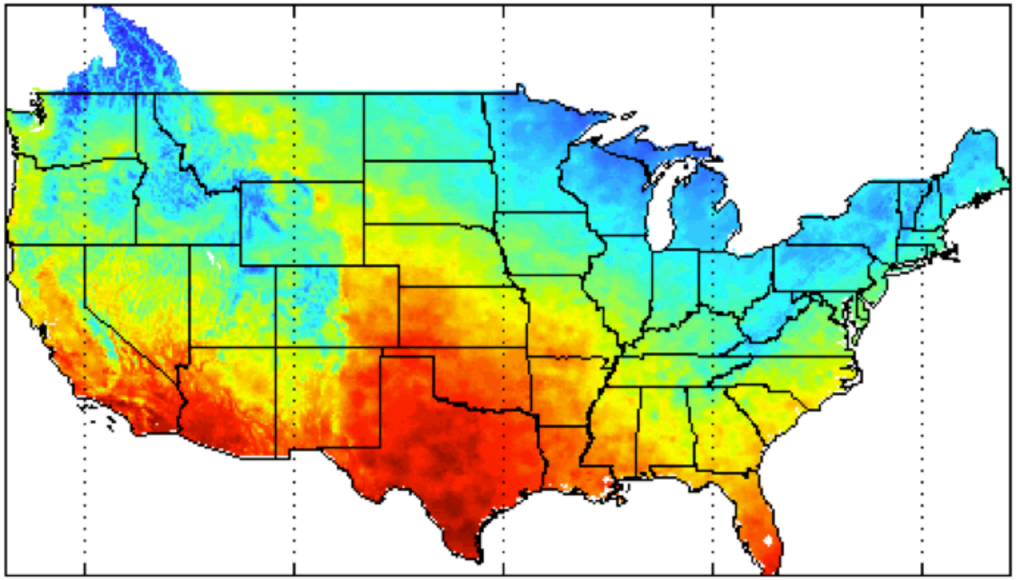
# Monthly weather inputs

Idaho observed climate dataset
*(Aldridge and Boyles)*

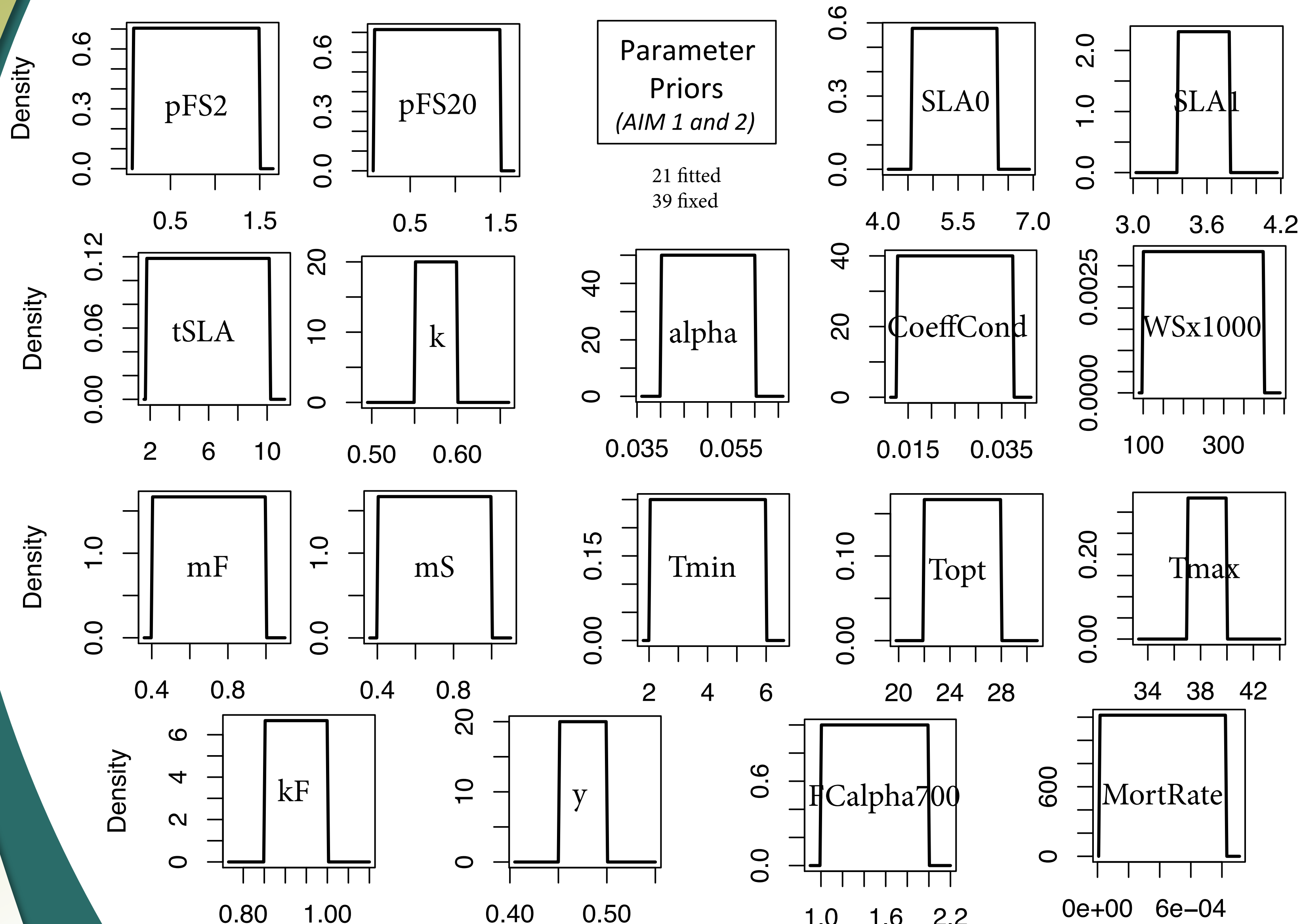
1979 – present

METDATA (Abatzoglou, 2013) with high spatial resolution (1/24-degree or approximately 4-km)

- Max. monthly temperature
- Min. monthly temperature
- Total monthly precipitation
- Monthly mean solar radiation
- #of days per month with min. temperature < 0

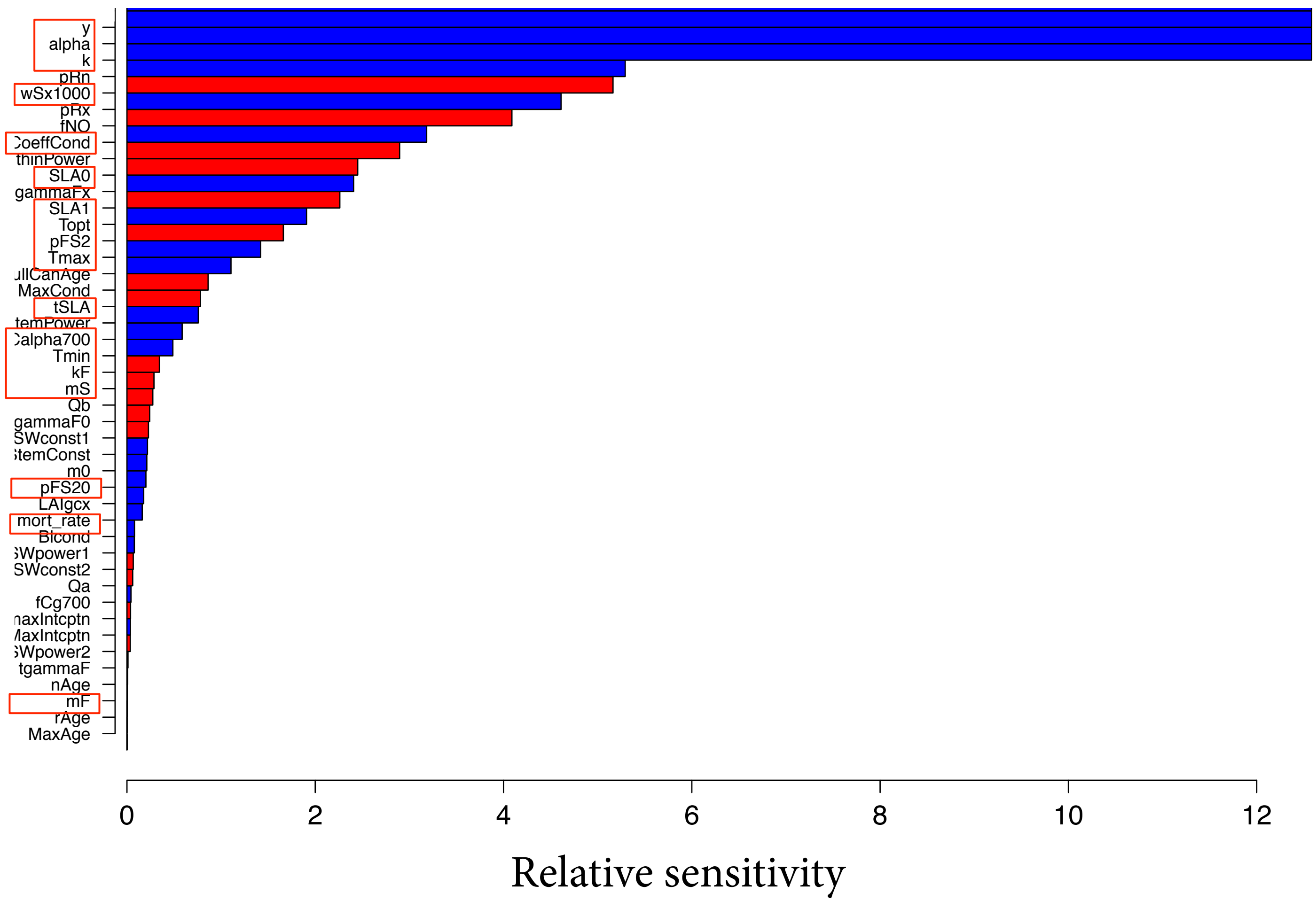


# Parameter priors

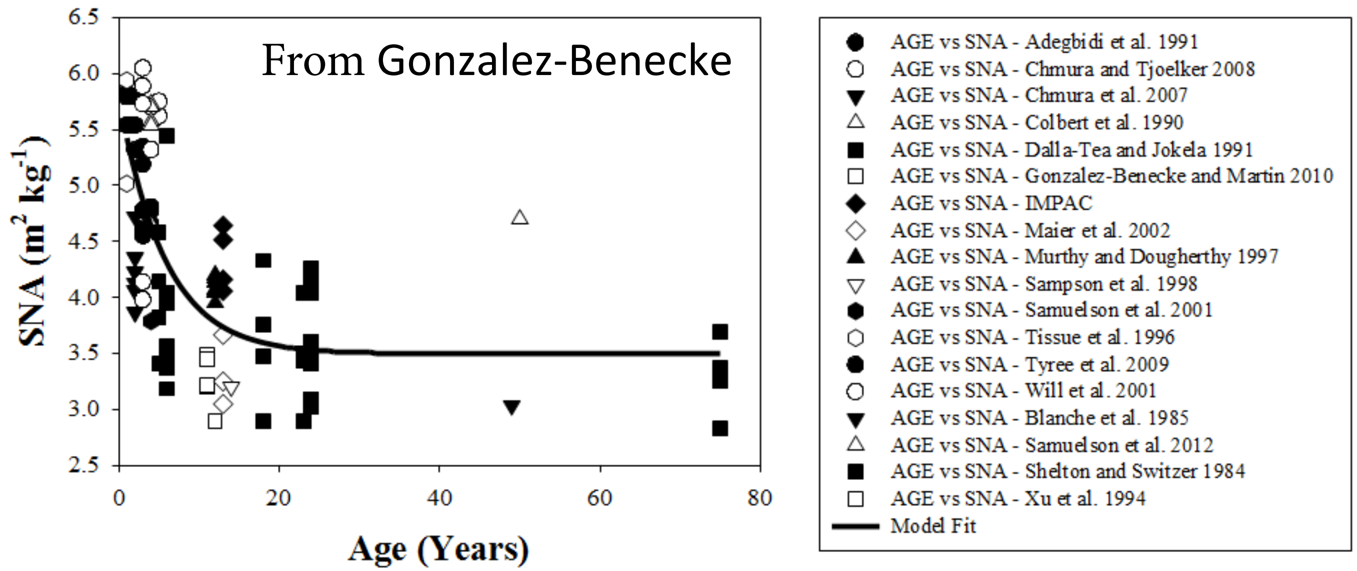


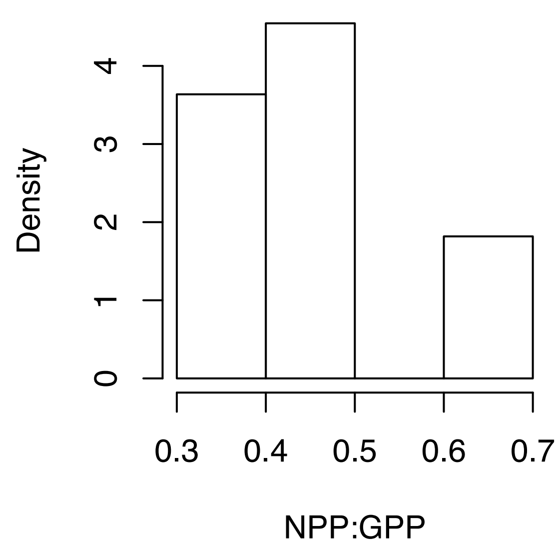
# Focusing on the most sensitive parameters

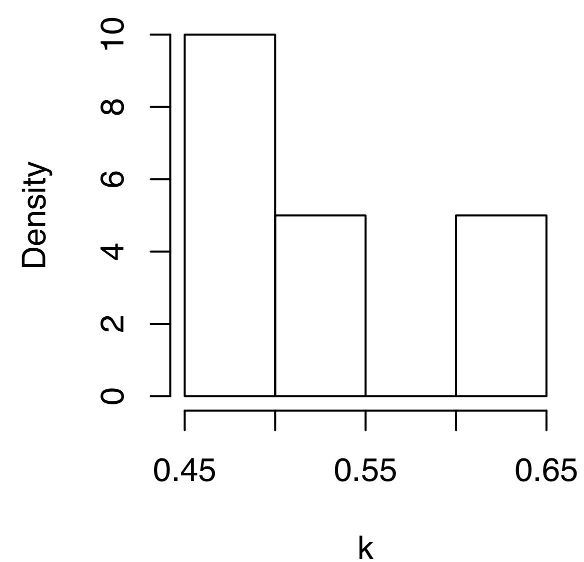
Clay Word (PINEMAP Intern)



# Parameter priors



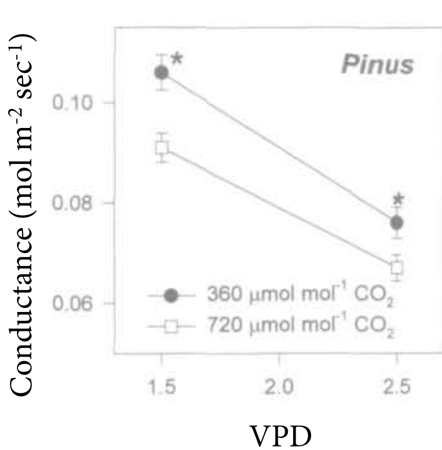



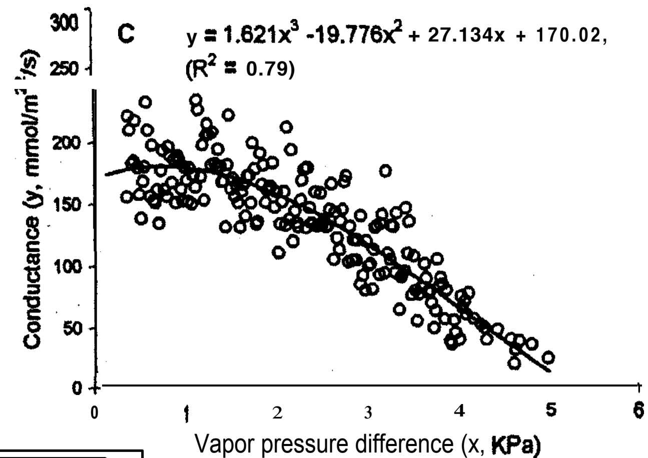
# Climate parameter priors

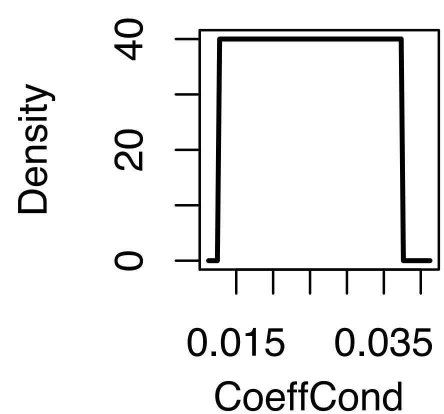
Fixed physiological parameters in the 3-PG model produced accurate estimates of loblolly pine growth on sites in different geographic regions

Charles Bryars [a], Chris Maier [b], Dehai Zhao [a], Michael Kane [a], Bruce Borders [a], Rodney Will [c], Robert Teskey [a,*]

[a] Warnell School of Forestry and Natural Resources, University of Georgia, 180 E. Green St. Athens, GA 30601, USA
[b] US Forest Service, Southern Research Station, SRS-4160, 3041 Cornwallis Road, Research Triangle Park, NC 27709, USA
[c] Natural Resource Ecology and Management, Oklahoma State University, 008C Ag Hall, Stillwater, OK 74077, USA




Tang et al 1999

Will and Teskey 1997

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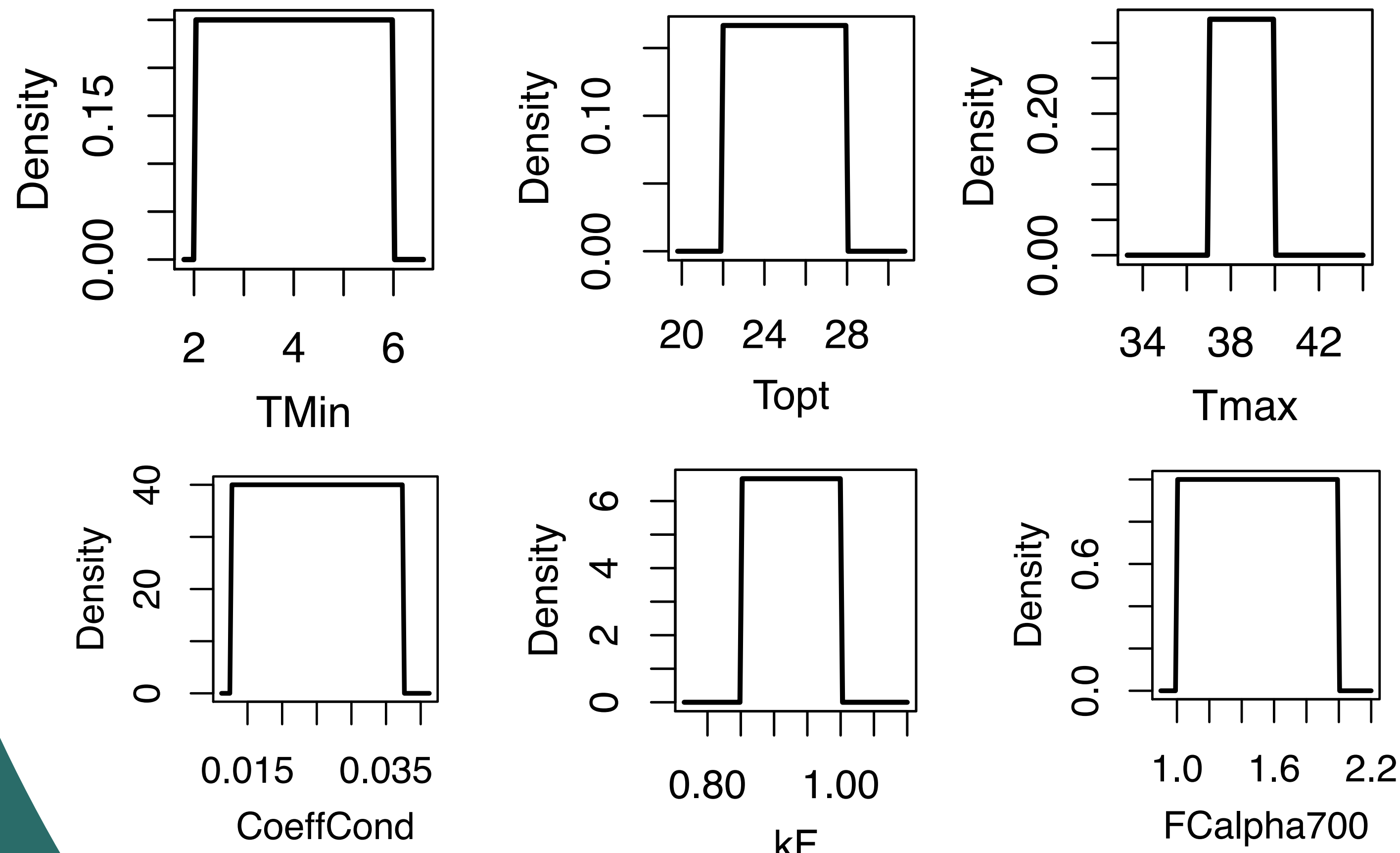
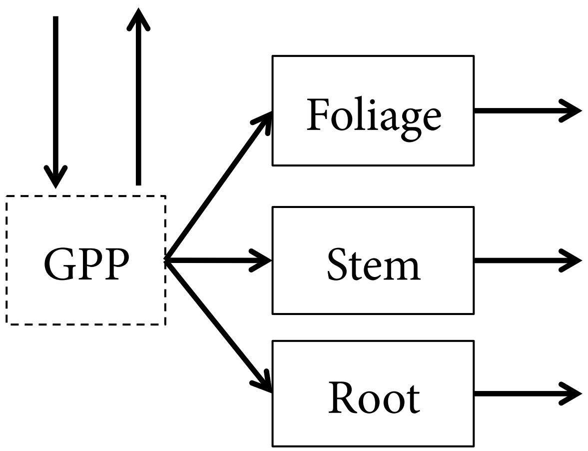


# 3PG model

3PG Model
in fortran with parallel
computing across plots
*(3PG modeling group)*

Landsberg-Sands version

- Added a parameter for density independent mortality (previously hardwired in code)
- Pulled out soil sensitivity parameters (previously hardwired in code)
- Fortran sub-routine called from R
- R does the modeling fitting
- Runs plots on different cores in parallel



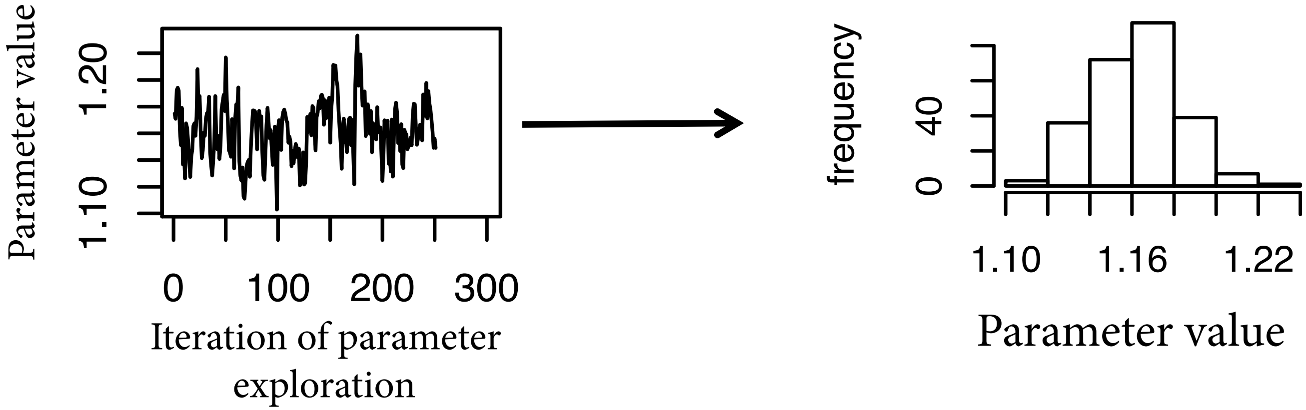
# Data-assimilation algorithm

Data assimilation
(MCMC-MH)
*(Thomas and Jersild)*

Widely-used Monte Carlo Markov chain – Metropolis Hastings algorithm

Explores parameter space:

- Accepts parameters sets that are better than previous set
- Accepts worse parameters proportional to how much worse they are
- Millions of iterations are necessary
- Runs for a week on VT Center for Environmental Applications of Remote Sensing computers

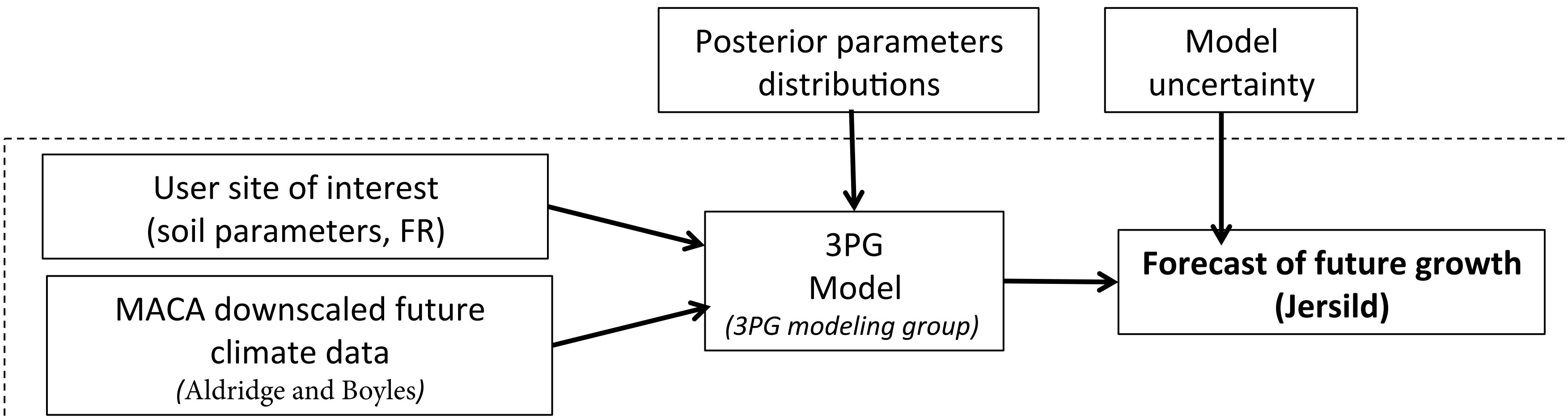


# Parameter and model uncertainty

- Parameter distribution and their co-variation
  - For example, a low value of parameter X may be always associated with a high value of parameter Y
- Use bootstrapping methods to
  - Calculate parameter uncertainty: Integrate across parameter distributions (accounts for co-variation)
  - Calculate model error uncertainty: Integrate across estimated distribution of model error (based on estimate standard deviation of error distribution)

# Forecasts

Forecasts incorporate parameter, model, climate, and scenario uncertainty




- Future climate from 20 different climate models
- Two RCP scenarios (4.5 and 8.5)
- FR and soils for a site need to be specified by the user

# Forecasts

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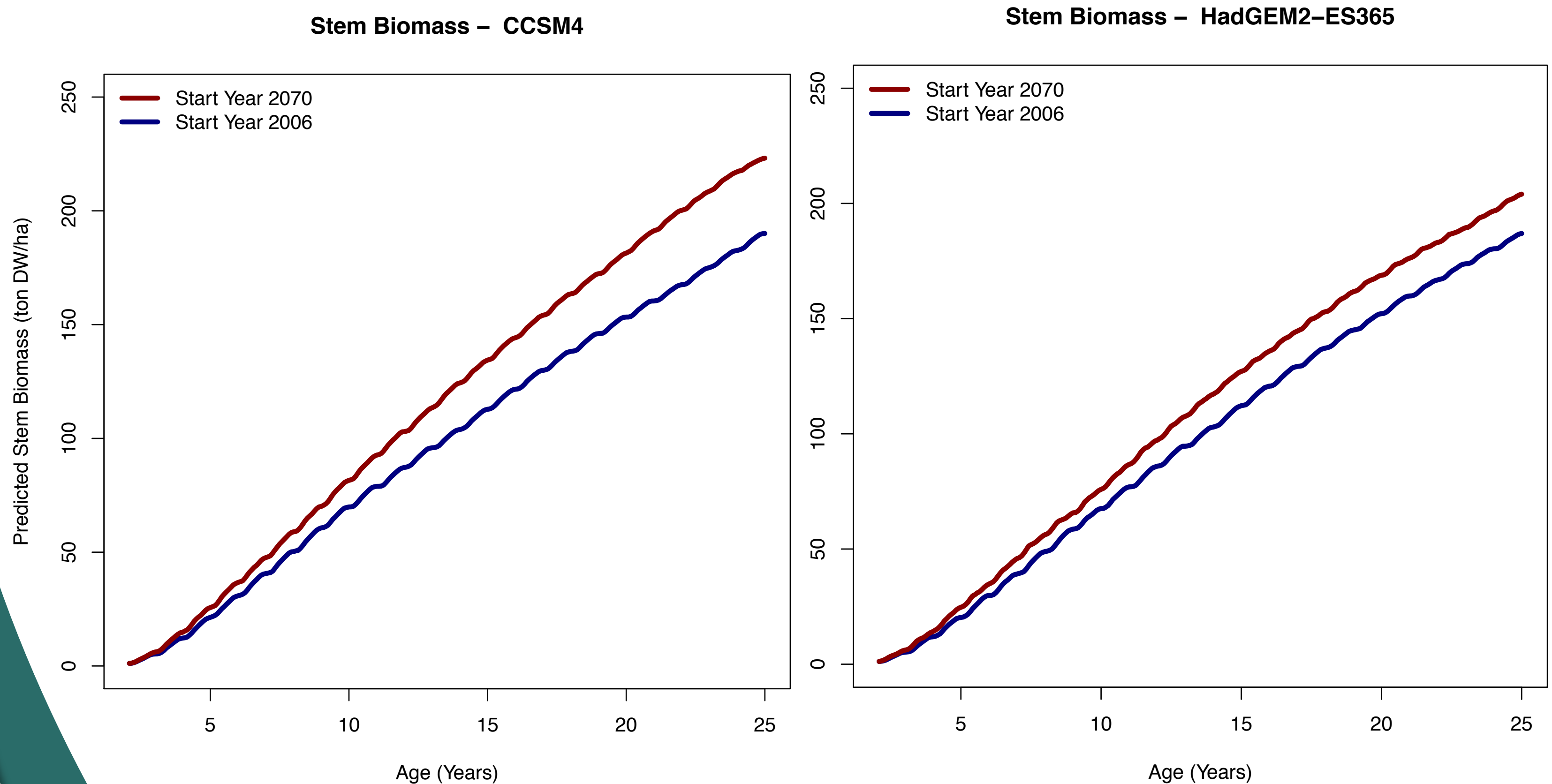

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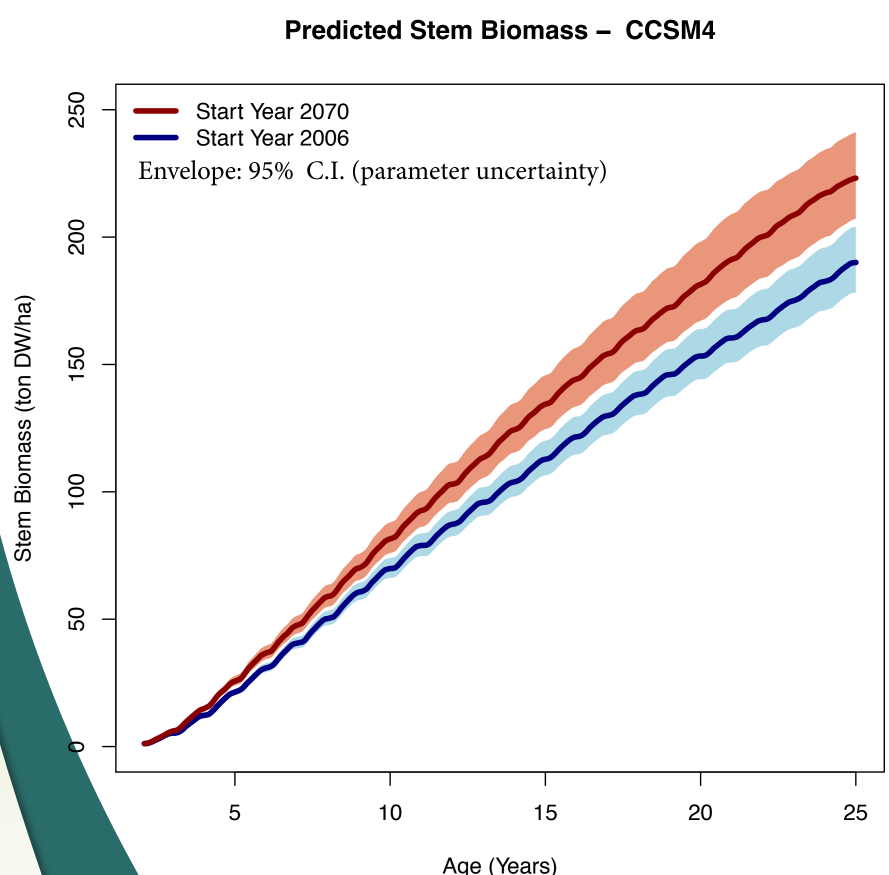
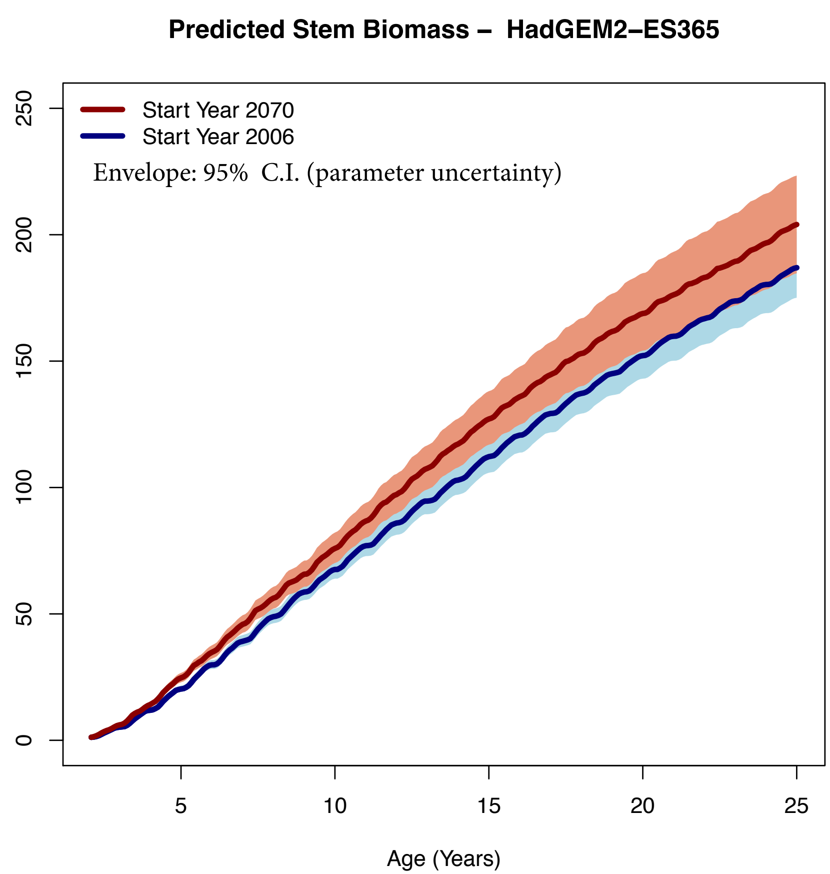
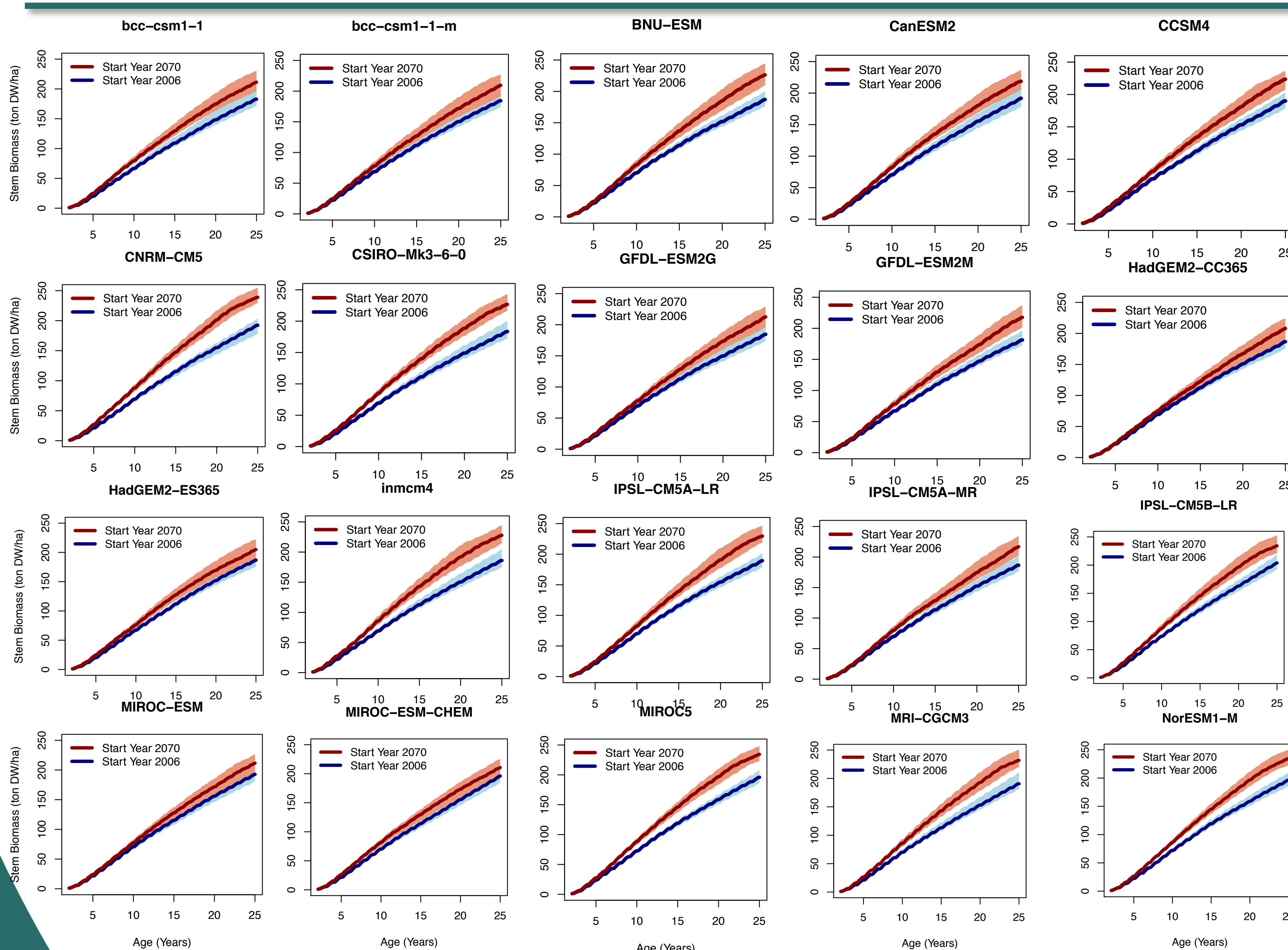


# Forecasts: RCP 8.5



# What are our new capacities?

- As before we can assess the response of a stand to future climate and $CO_2$
- In addition we can address the following:
  - What is the probability that future climate and $CO_2$ will increase growth?
  - What is the probability of stand X having biomass Y at age 25 in year 2050?
  - What is the relative contribution of parameter X to the total uncertainty?
  - What year in the future to we expect the signal of increased growth to emerge from the noise of uncertainty?

# Next steps

- Better water cycle
  - Eric Ward and I are working on building in transpiration estimates from Tier 3, Duke, and NC Flux tower
- Better root dynamics
  - Currently, root parameters are fixed because region-wide observations are lacking
- Add additional Tier 1 and 2 plots to better constrain key processes
  - Plots where FR can be assumed to be 1 are critical.
- Improve computational efficiency to allow for more plots to be added

# Upcoming

- Three AGU oral talks in the session:
  - "Predicting future productivity of Southeastern U.S. pine ecosystems in a changing climate using data assimilation with diverse data sources" – Monday December 14 at 5:30 pm – Oral talk by Q. Thomas
  - "Relative role of parameter vs. climate uncertainty for predictions of future Southeastern U.S. pine carbon cycling" – Tuesday December 15 at 9:30 am – Oral talk by A. Jersild
  - "Incorporating Ecosystem Experiments and Observations into Process Models of Forest Carbon and Water Cycles: Challenges and Solutions" – Tuesday December 15 at 11:05 am – Oral talk by E. Ward