Land Modeling with Machine Learning: Parameter Sensitivity, Calibration, and Hybrid Modeling

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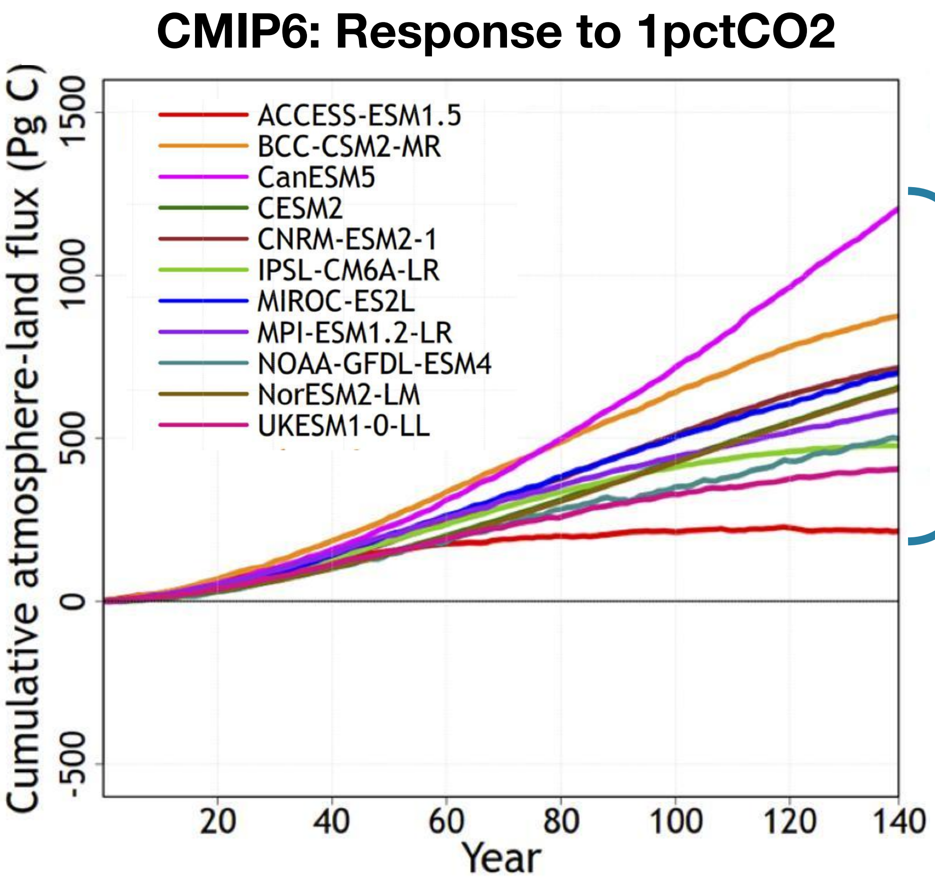
Carbon Cycle Uncertainty in Land Model Projections

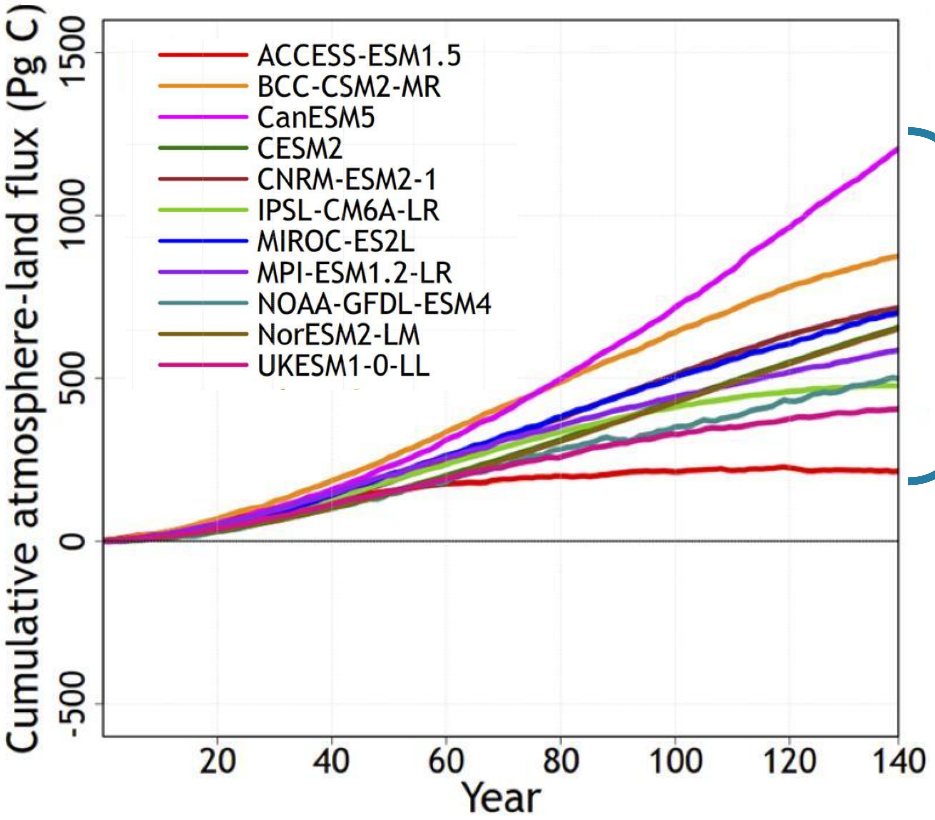


Strength of the land carbon sink:
~1000 Pg C spread,
or 100x global annual C emissions

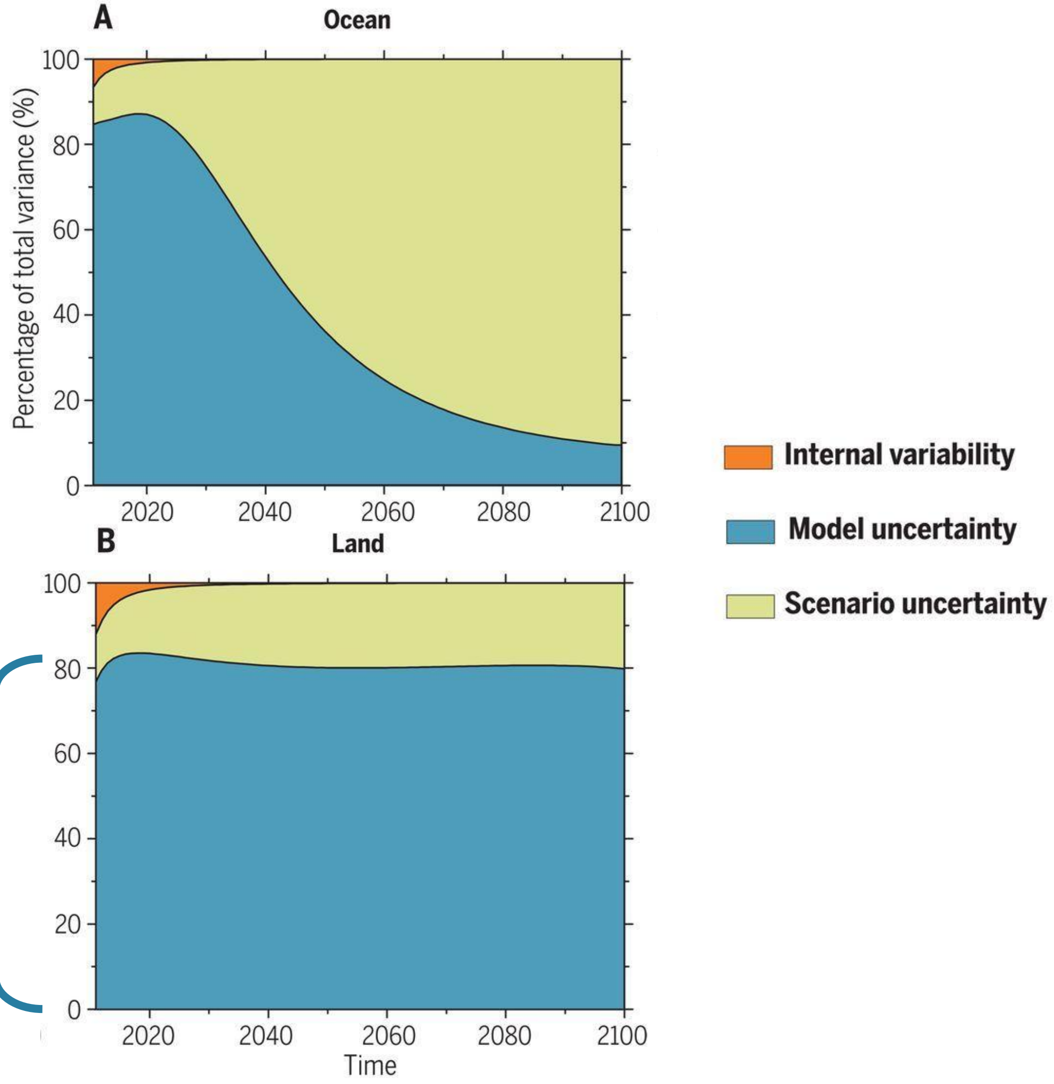
Arora et al. (2020)

Carbon Cycle Uncertainty in Land Model Projections

CMIP6: Response to 1pctCO2



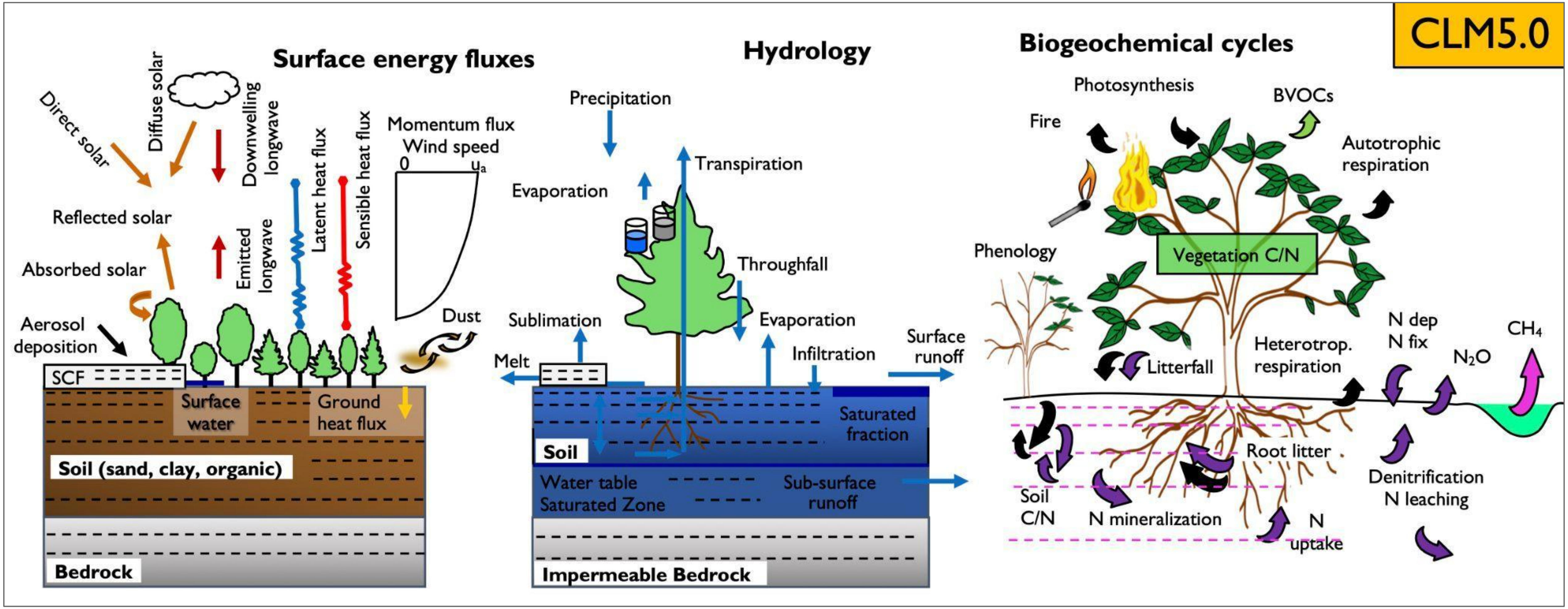
Uncertainty in land model structure and **parameters**



Arora et al. (2020)

Bonan and Doney (2018), based on Lovenduski and Bonan (2017)

Community Land Model (CLM) Parameters



Schematic of the Community Land Model (CLM), version 5

Lawrence et al. (2019)

Challenges for Land Model Calibration

Large & poorly constrained parameter space

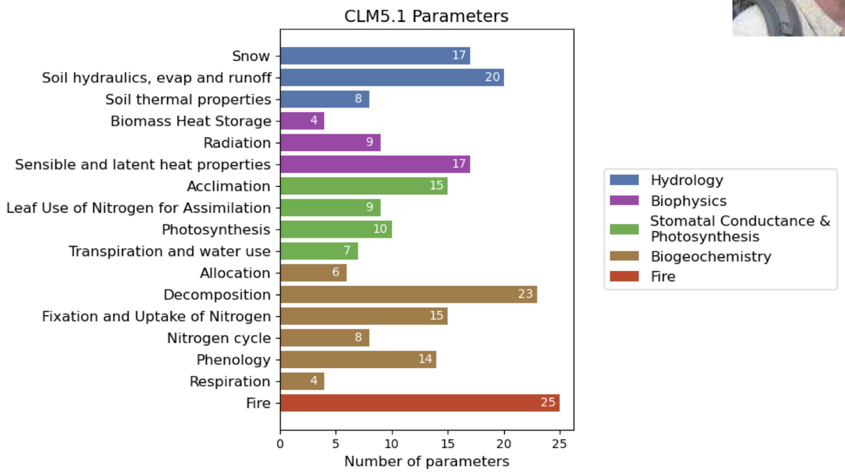
- CLM has over 200 parameters
- Complex interactions

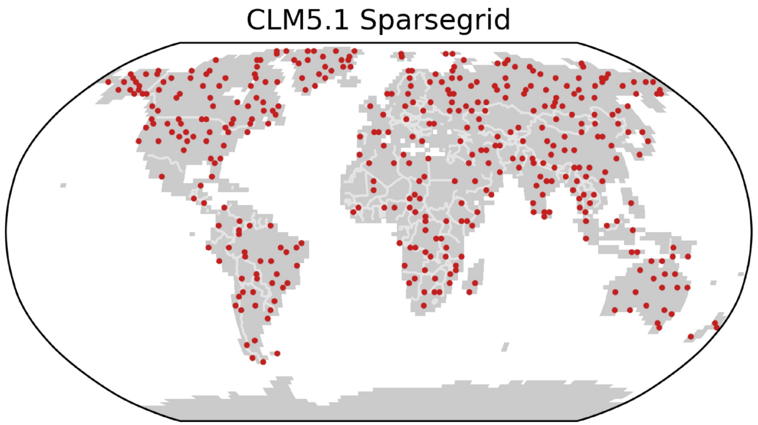
Plant functional types

- Unique parameter settings for each PFT

Computational expense

- Long carbon residence times
- Path dependence





Design a sparse grid using clustering
14x faster than equivalent 2deg model

Kennedy et al. (2025)

Land Model Systematic Parameter Calibration

Establish ML-based methodology for calibration of Earth System Model parameters

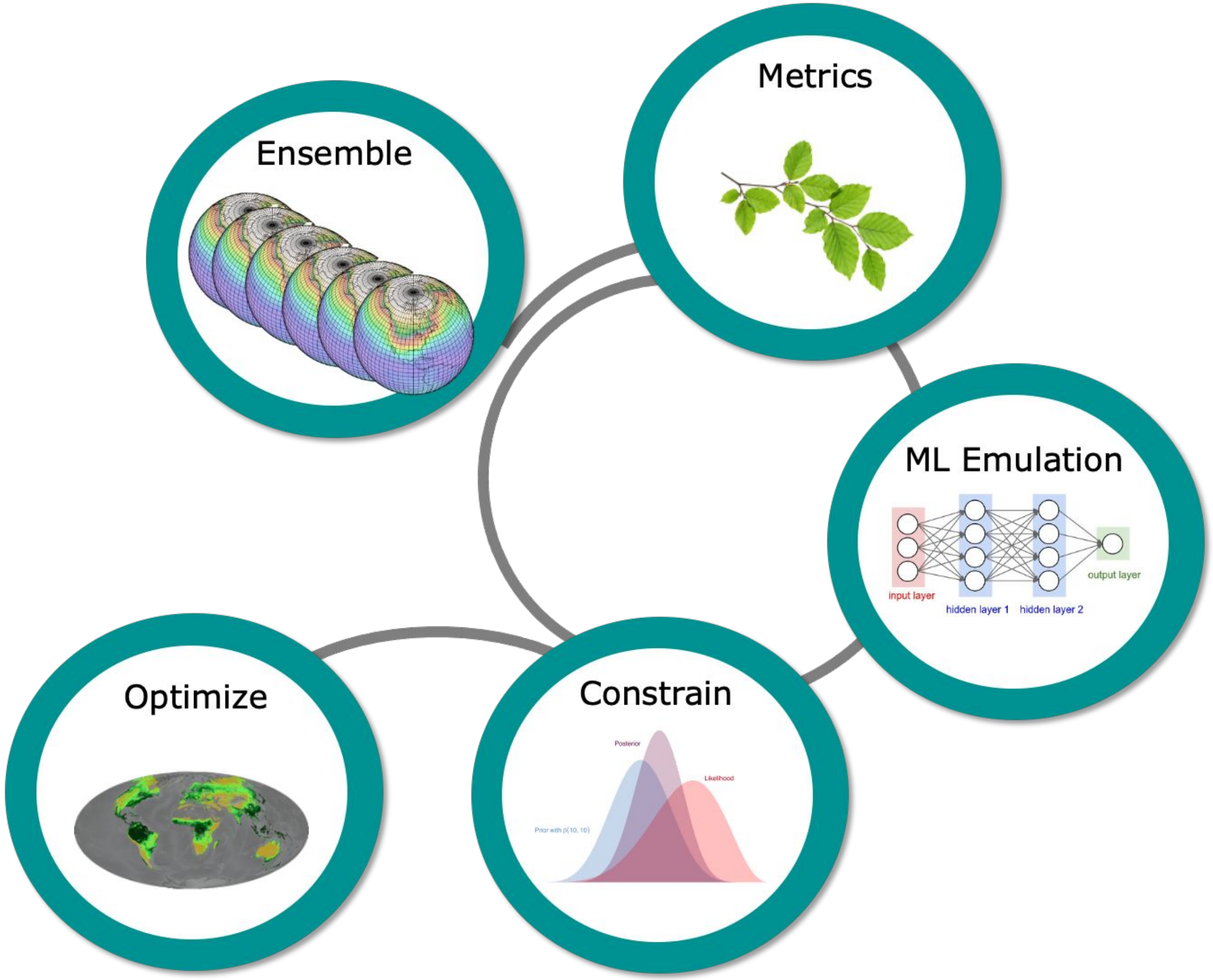


Figure from Linnia Hawkins

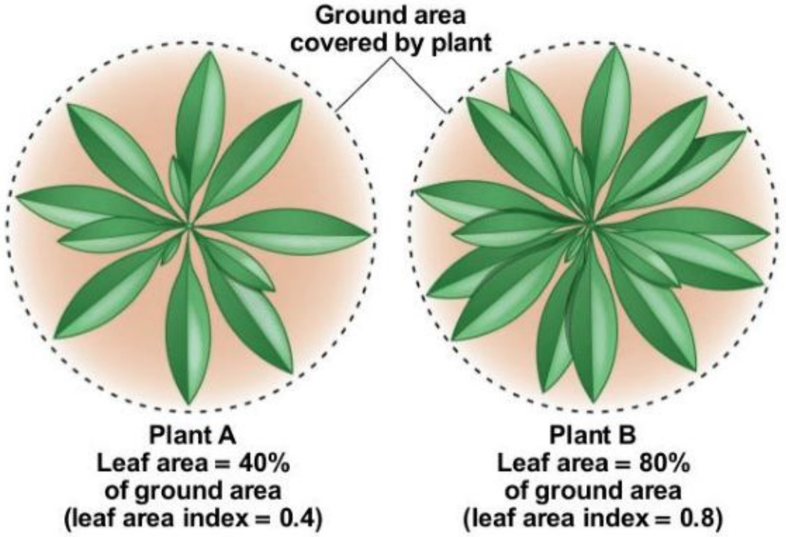
LEAP

https://leap.columbia.edu/

Ensemble Design

Multivariable Calibration:

- Leaf area index (LAI), gross primary production (GPP), and biomass
- Observational constraints



Pearson Education

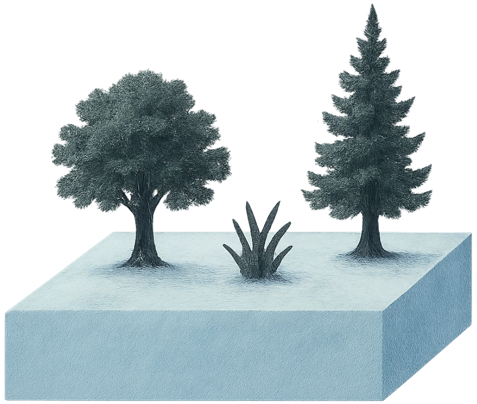
Experimental Design:

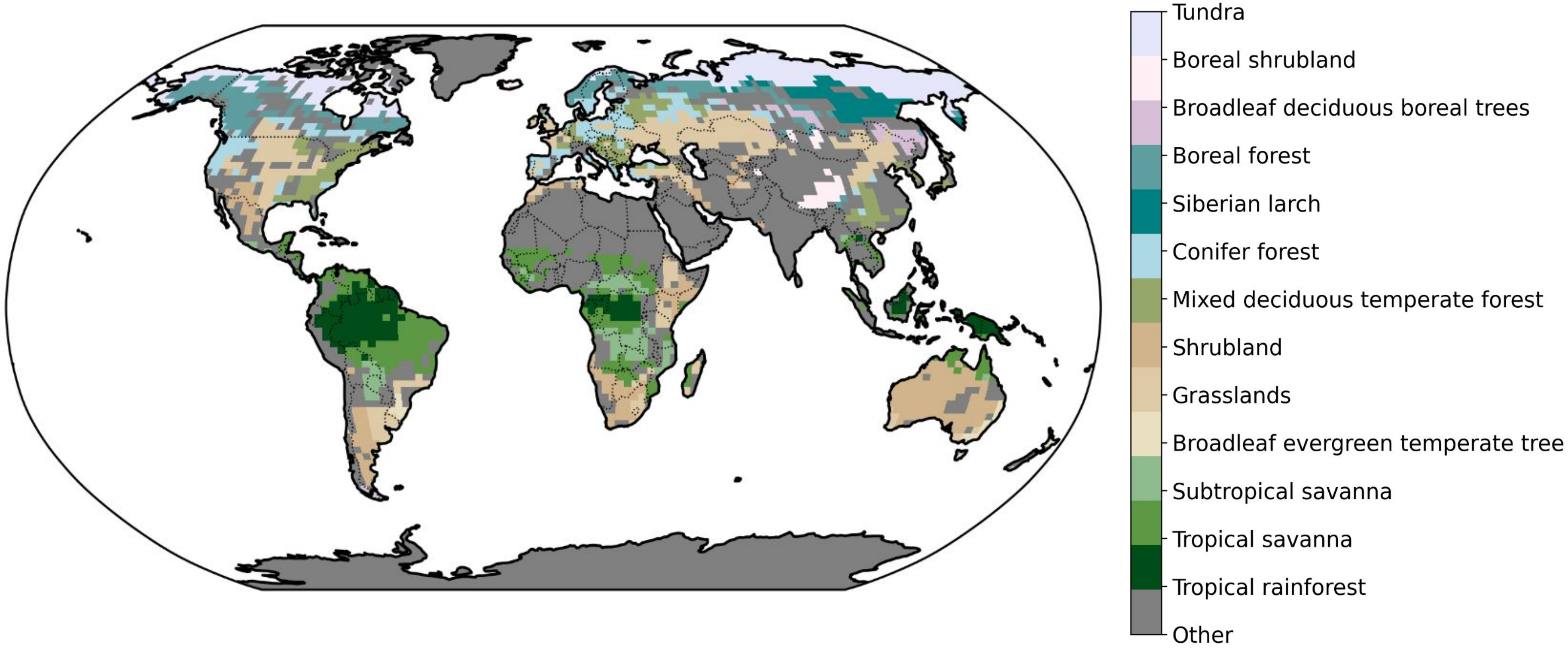
- Subset 56 relevant parameters in CLM6
- Latin hypercube sampling
- 1500 ensemble members
- Transient simulations (1850-2023)
  - *NEXT: projections to 2100*
- Global land-only; atmospheric forcing

Target Metrics to Account for Spatial Variation

Metrics

- Designed biomes where only a few plant functional types (PFTs) coexist
- Allows for independent PFT parameter tuning and captures PFT interactions





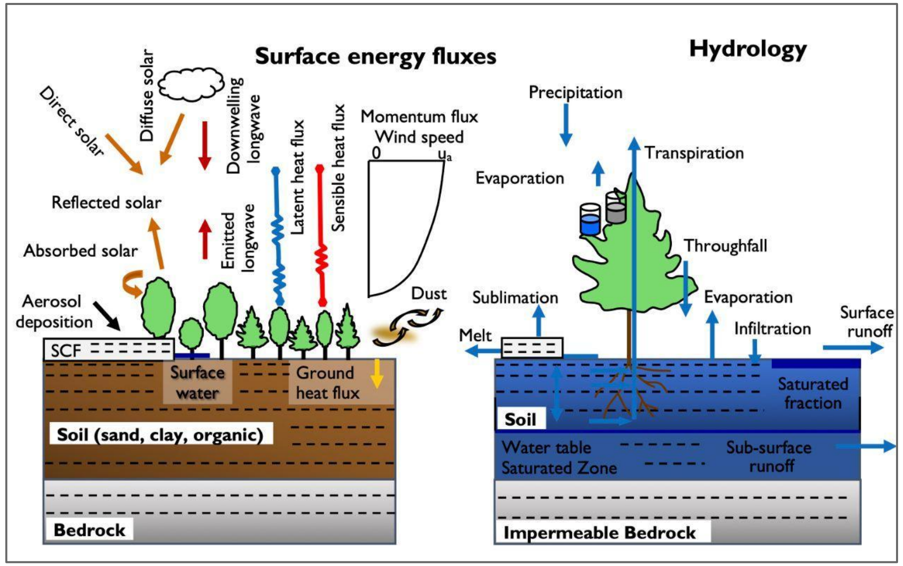
ML Emulation

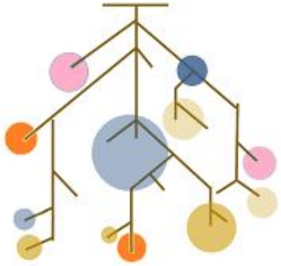
Training the Emulators

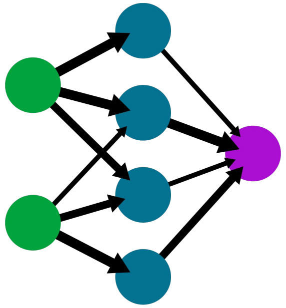
Input: **CLM parameter values**

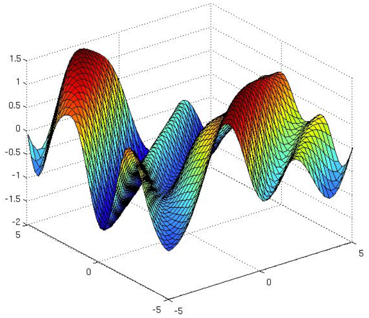
Machine learning emulator
(e.g., neural network, random forest, gaussian process model)

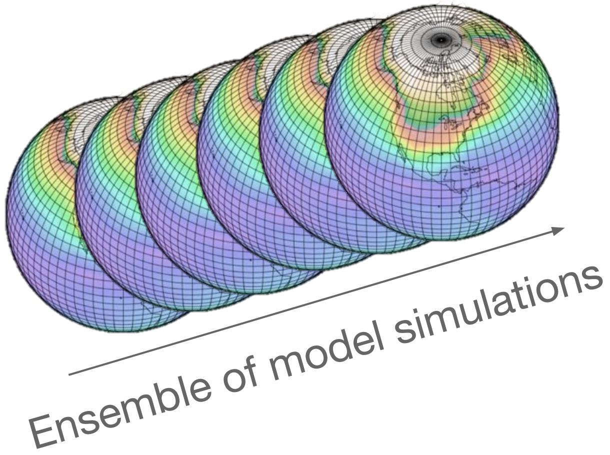
Output: **spatial biome mean** of **target variable**





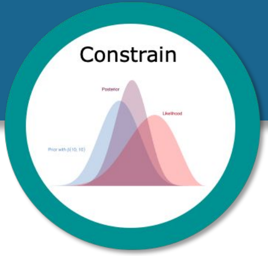






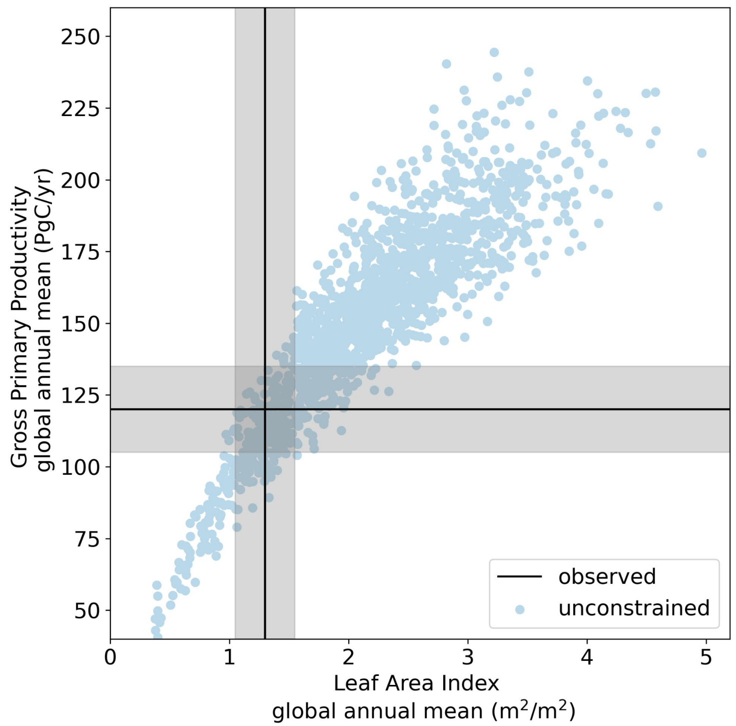
Learning the parameter response functions

NN: Dagon et al. (2020)
GP: Hawkins et al. *in prep*

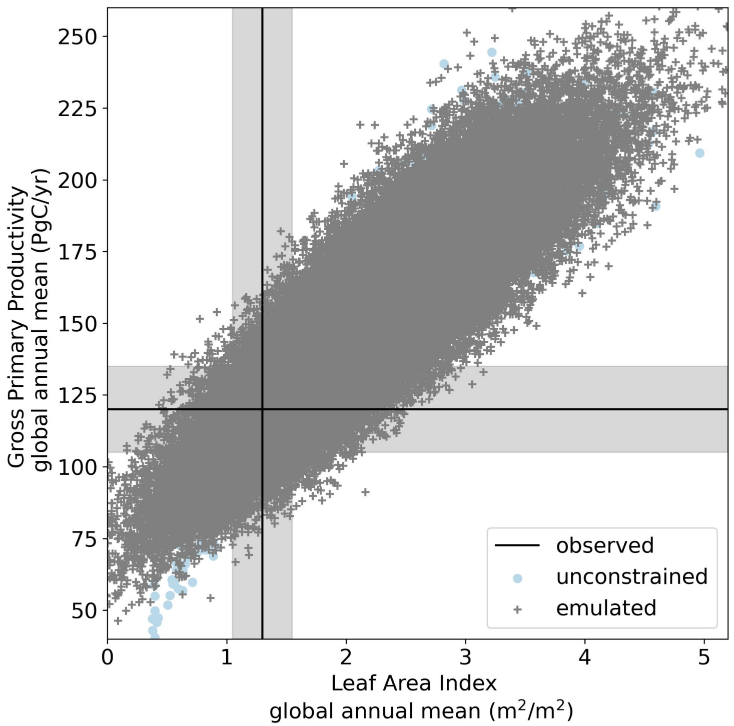


History Matching

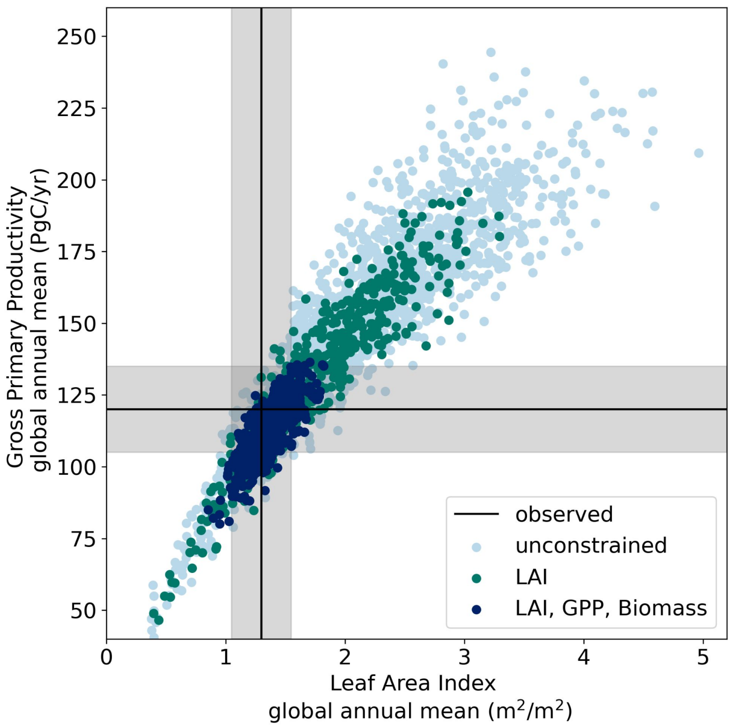
Simulate



Emulate

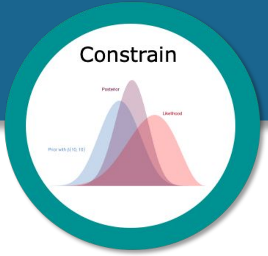


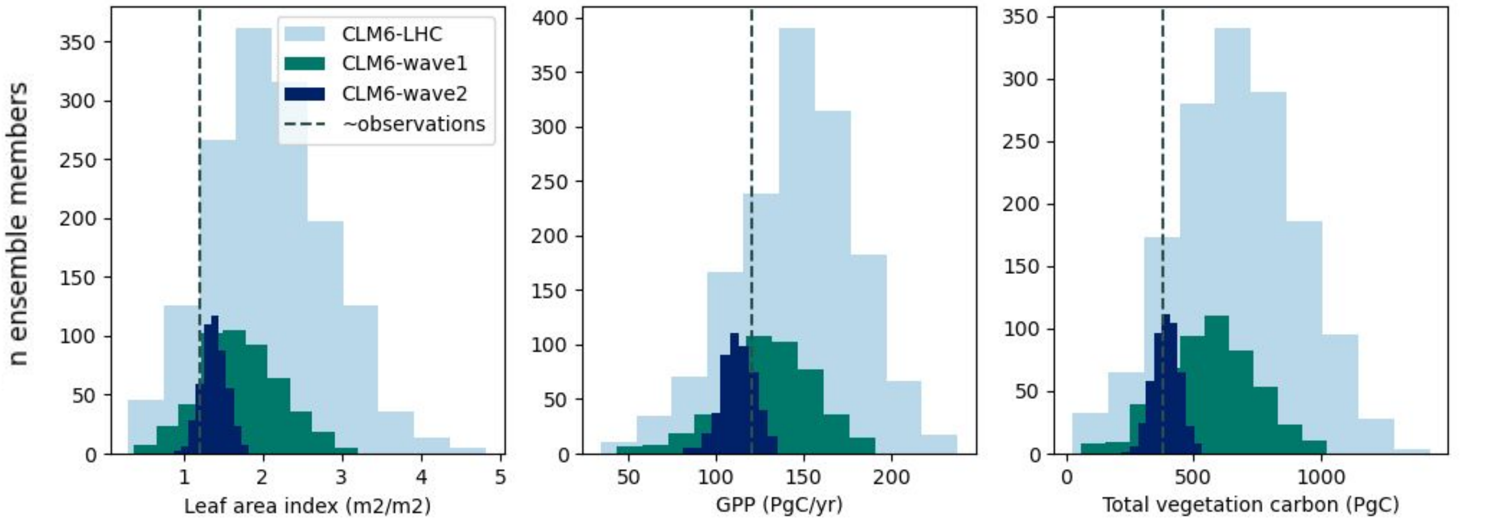
Constrain



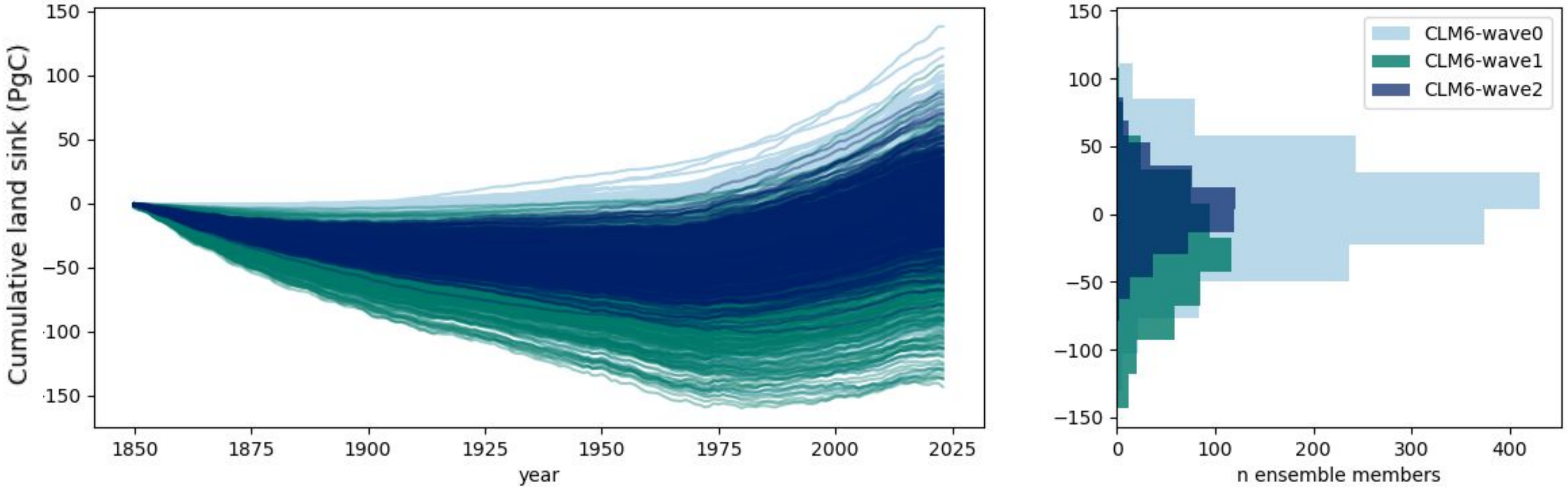
- Rule out implausible parameter sets
- Can do history matching in “waves”

History Matching





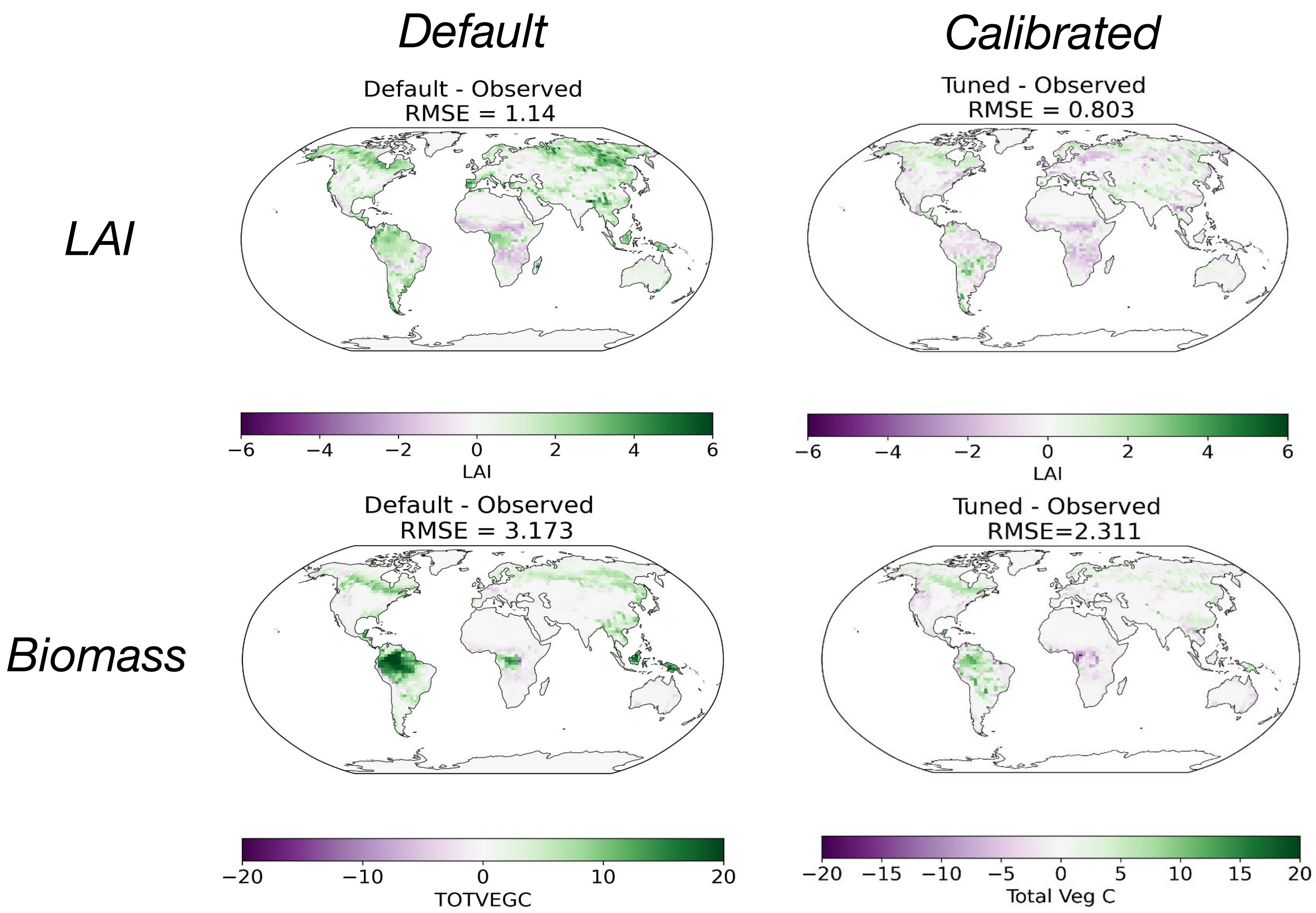
Unconstrained
Leaf Area Index
LAI, GPP, Biomass

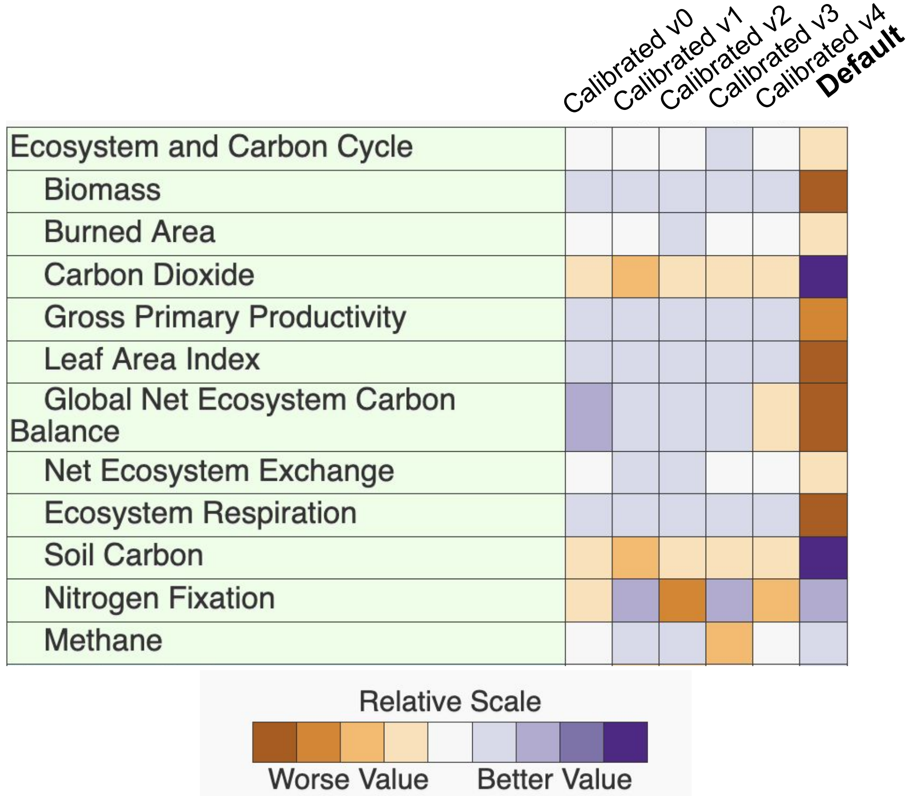


Narrowing the land carbon sink spread from ~250 to 100 Pg C

Calibration

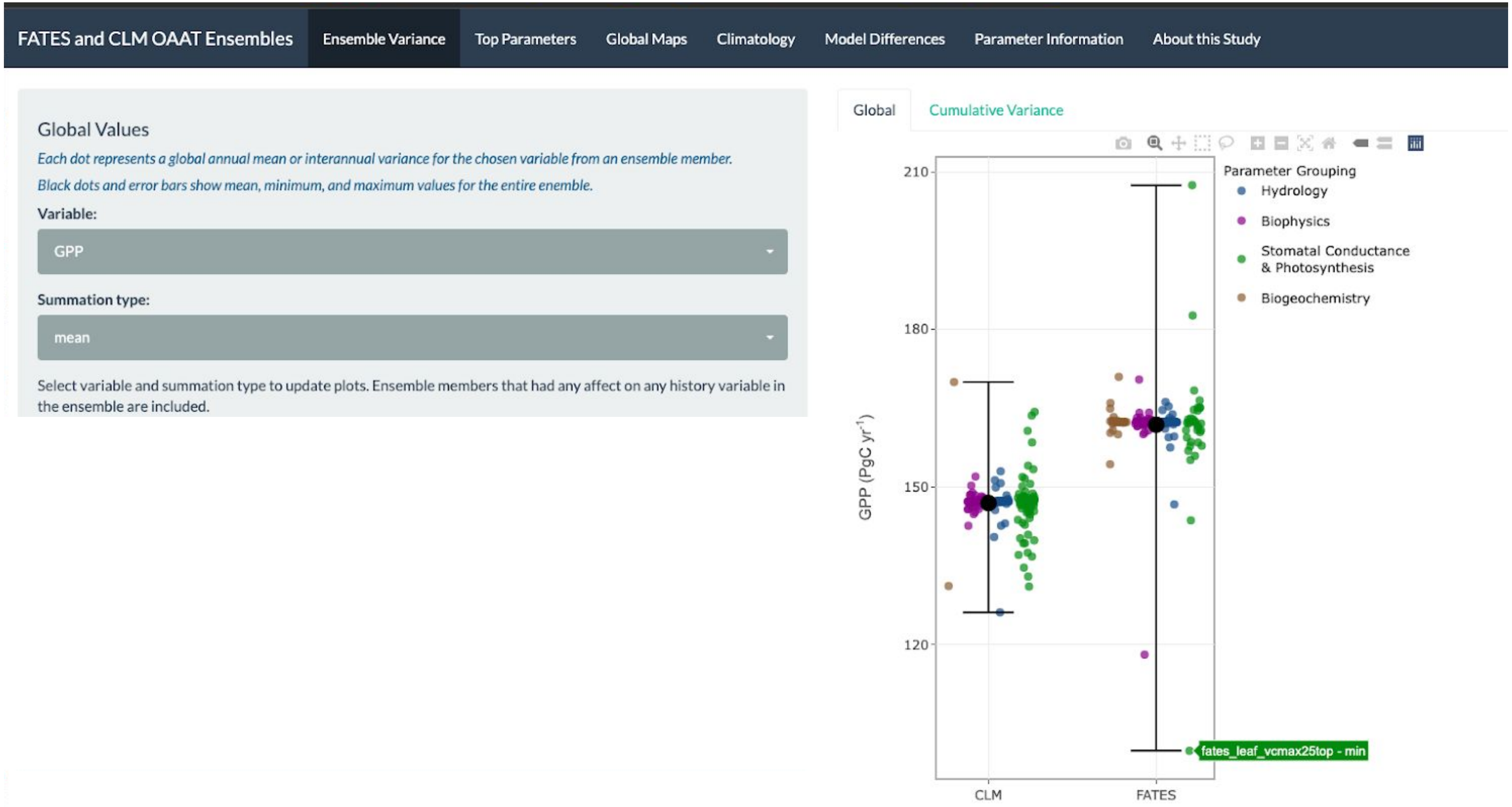
- Align model output with observational constraints across diverse ecosystems
- Don’t mess anything else up (i.e., stay close to the default parameter values)





ILAMB.org

Visualization



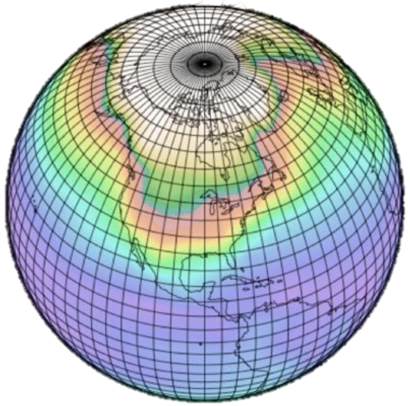
https://gpxqz5-adrianna-foster.shinyapps.io/shiny_app/

Developed by Adrianna Foster

Enabling New Science

- Arctic hydrology (Cheng, NCAR-RAL/U. Buffalo)
- CONUS streamflow (Yan, PNNL; **Eldardiry**, PNNL)
- Emulating seasonal cycle (**Kumar**, Auburn Univ.)
- ET drivers (**Buchovecky**, Univ. Washington)
- FATES PPE (Foster, NCAR)
- Land-atmosphere interactions (**Zarakas**, Univ. Washington; **Bouman**, DLR Germany)
- NEON site calibration (**Kavoo**, Auburn Univ.)
- Runoff sensitivity (**Elkouk**, Michigan State; **Kim**, Cornell Univ.)
- Tropical carbon cycle interannual variability (**Huang**, NCAR/JPL)

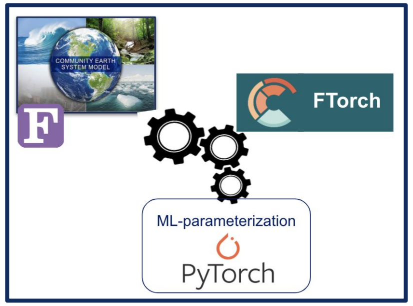
BOLD = student/postdoc project



NCAR / **ctsm6_ppe**

NCAR / **ctsm_ppe_analysis**

Hybrid Modeling for CESM3-MLe



Radiation

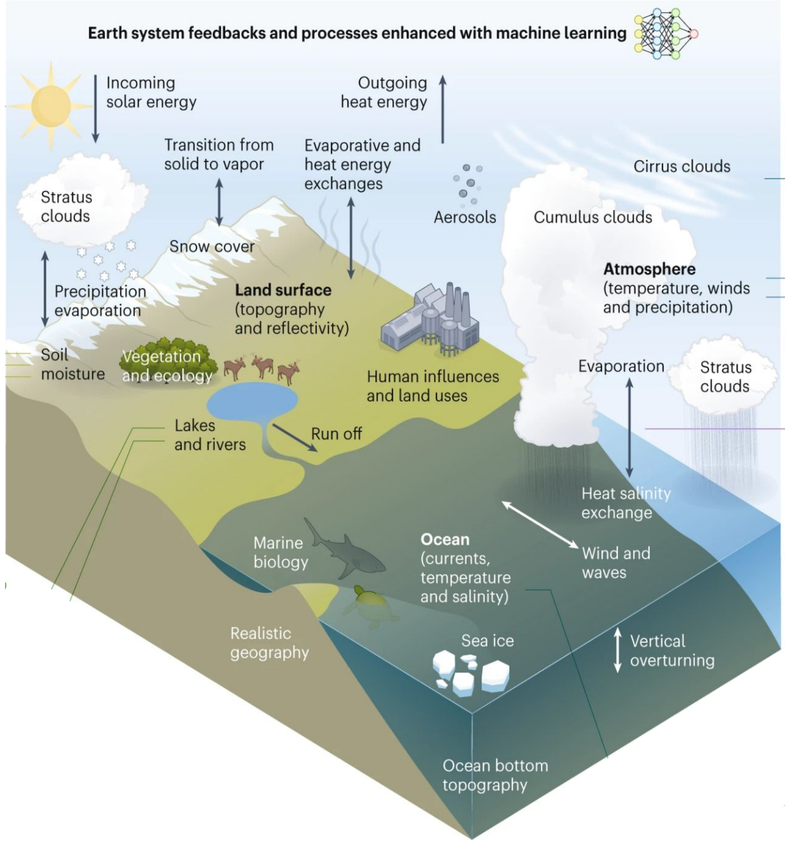
Phenology

Pedotransfer functions

Fire

Sea ice heat conduction

Ice sheet friction



Warm rain microphysics

Ice microphysics

Turbulence

Convection

Cloud cover

Atmospheric Chemistry

Vertical Mixing (KPP)

Ocean Mesoscales

Air-sea turbulent fluxes

LEAP

M^2LInES

ICON, E3SM, lit.

ML-based calibration, parametric and structural uncertainty quantification

Figure modified from Eyring et al. 2024

Summary

- Land models have **large parametric and structural uncertainties**, which impact assessment of emergent climate features such as the **land carbon sink.**

- **Machine learning emulation** and history matching used to calibrate a global land model; applicable to **model development** and **science questions.**

- Other opportunities for ML in land modeling include **spin-up** and **hybrid modeling.**

- **Domain knowledge combined with ML** made this work possible!

Thanks!
Questions?

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