Tuning CLM6:
Systematically constraining parametric uncertainty

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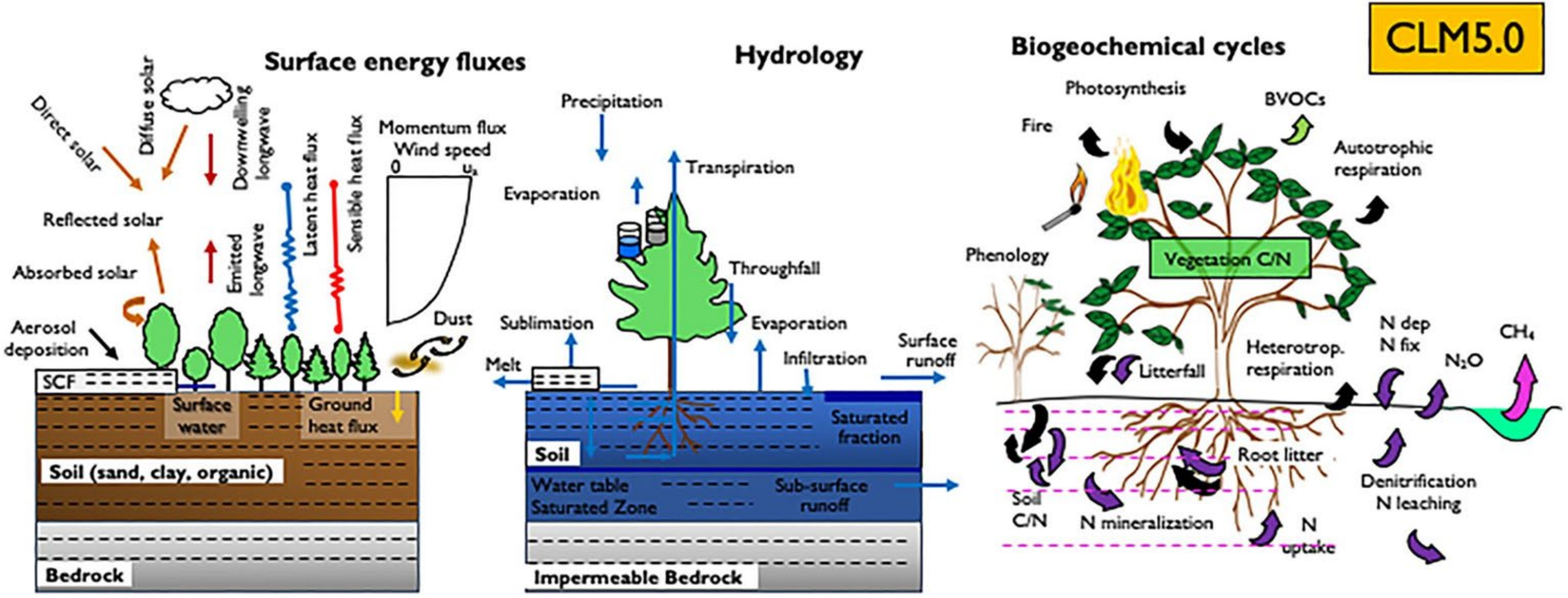
CLM-PPE community

CLM simulates far more processes than are observed



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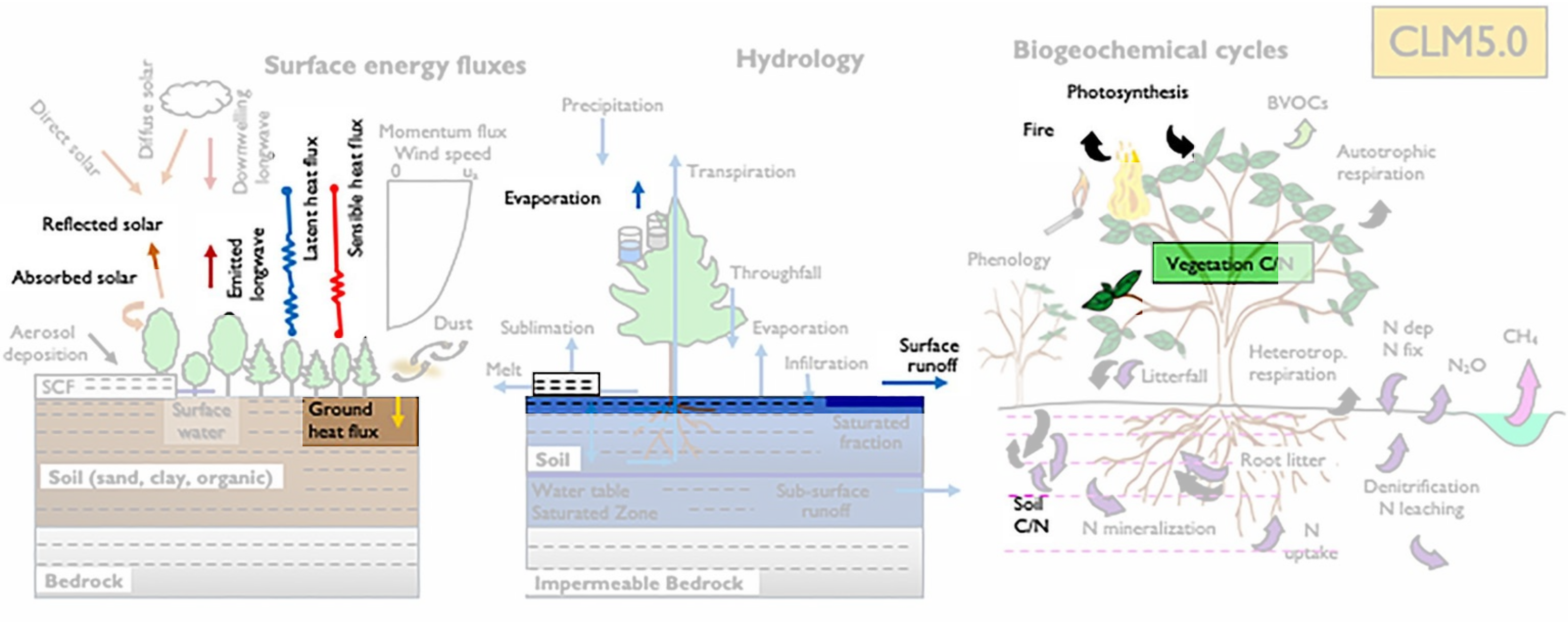


LEAP

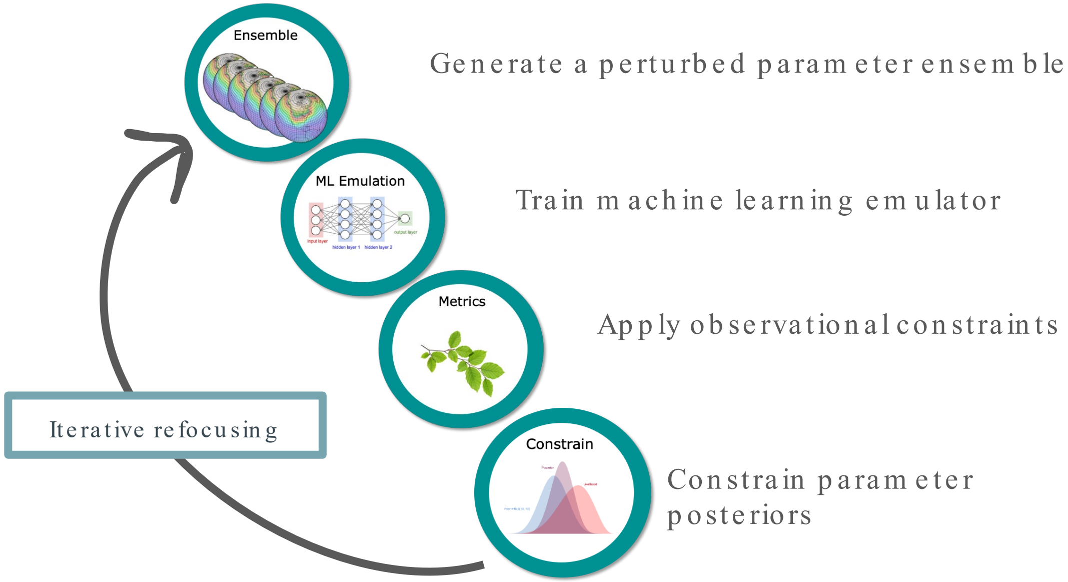
History Matching

Latin hypercube sample
56 parameters
1500 members

Wave 1
PFT Leaf Area Index
500 members

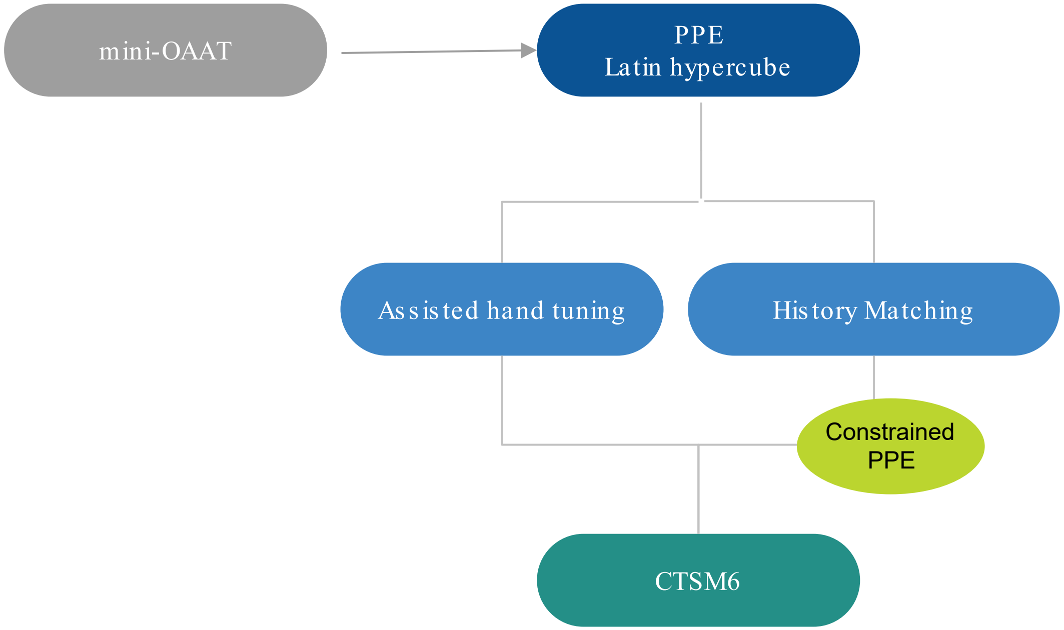
Wave 2
GPP, LAI, ET, Biomass
500 members

Constrained PPE



Experimental design

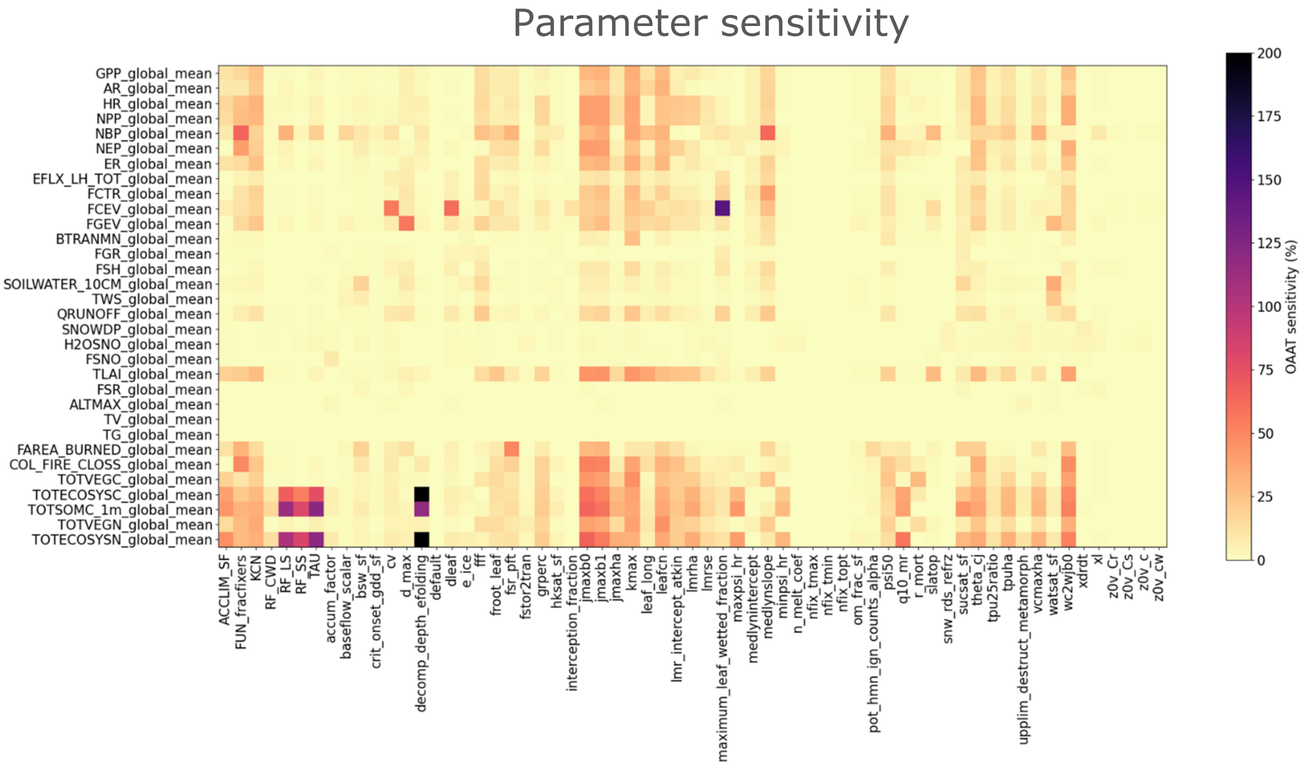
Objective 1: Tuning CTSM6
Objective 2: Carbon cycle uncertainty quantification



One-at-a-time ensemble

- 76 Parameters
- Min, Max

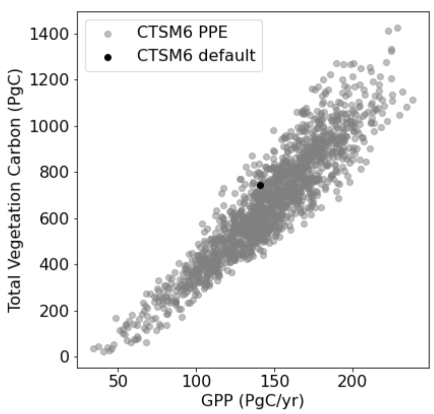
- Transient (1850-2023)
- CRUJRA forcing
- Sparse grid

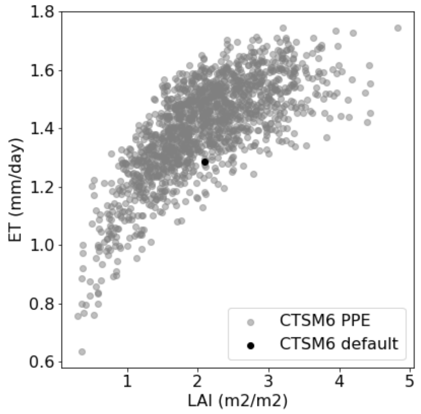


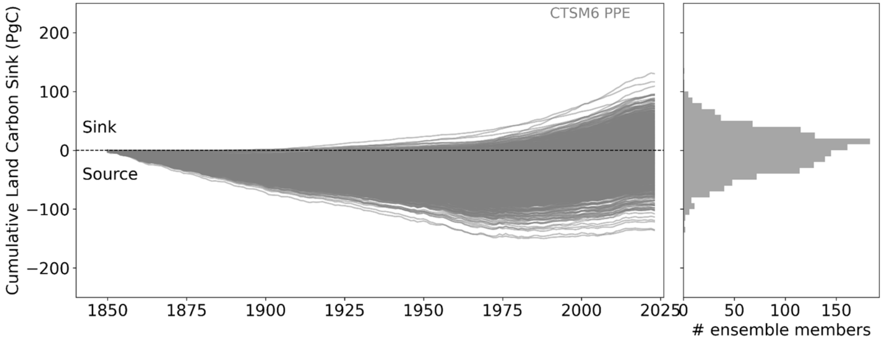
Perturbed parameter ensemble (PPE)

- 56 parameters
- 1500 ensemble members
- Latin hypercube sampling design

- Sparse grid
- Spin-up + 1850-2023
- CRUJRA forcing

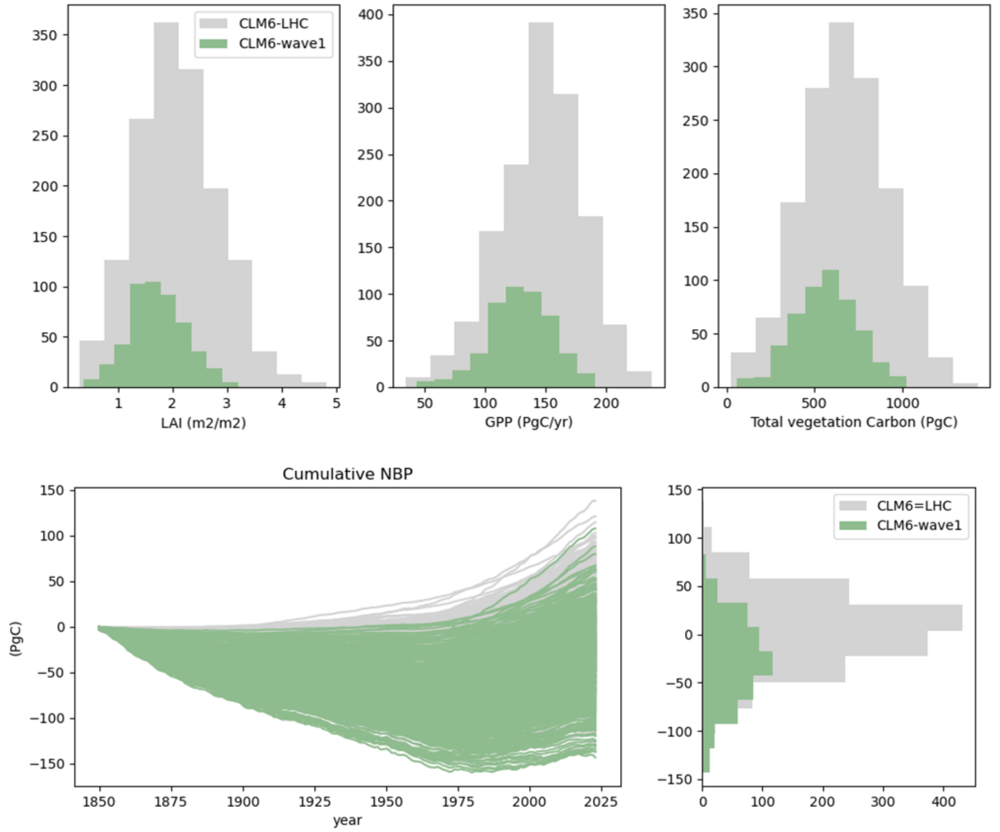






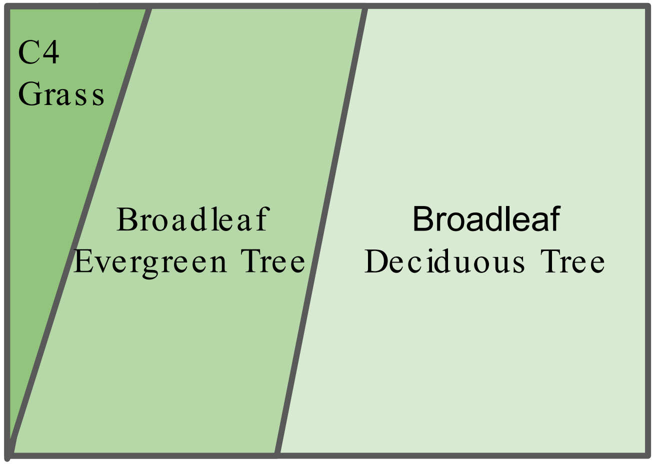
Wave 1

- 15 independent PFT parameters
- PFT mean LAI
- Observational target: CLM-SP
- 500 ensemble members

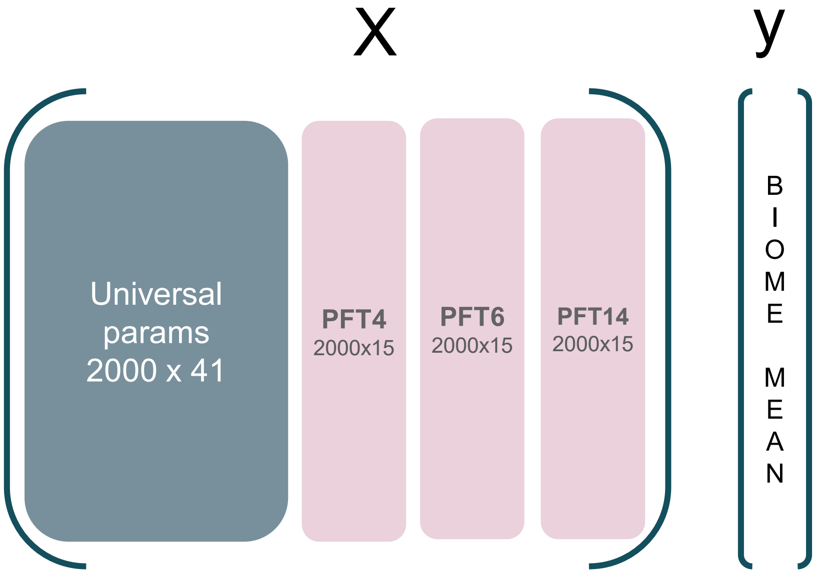


Wave 2

- Tune PFT parameters independently
- Gridded data products
  - GPP, LAI, Biomass, ET



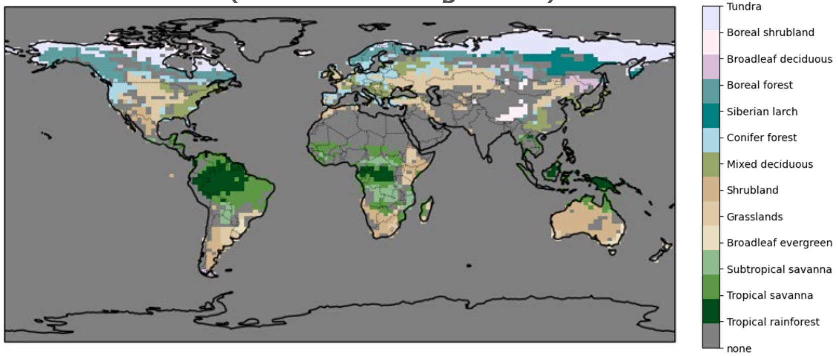
Fractional coverage in a gridcell



Wave 2

- Tune PFT parameters independently
- Gridded data products
    - GPP, LAI, Biomass, ET

Biomes (<5 coexisting PFTs)

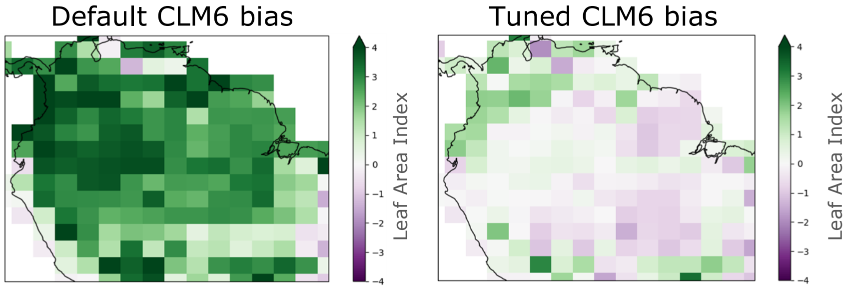


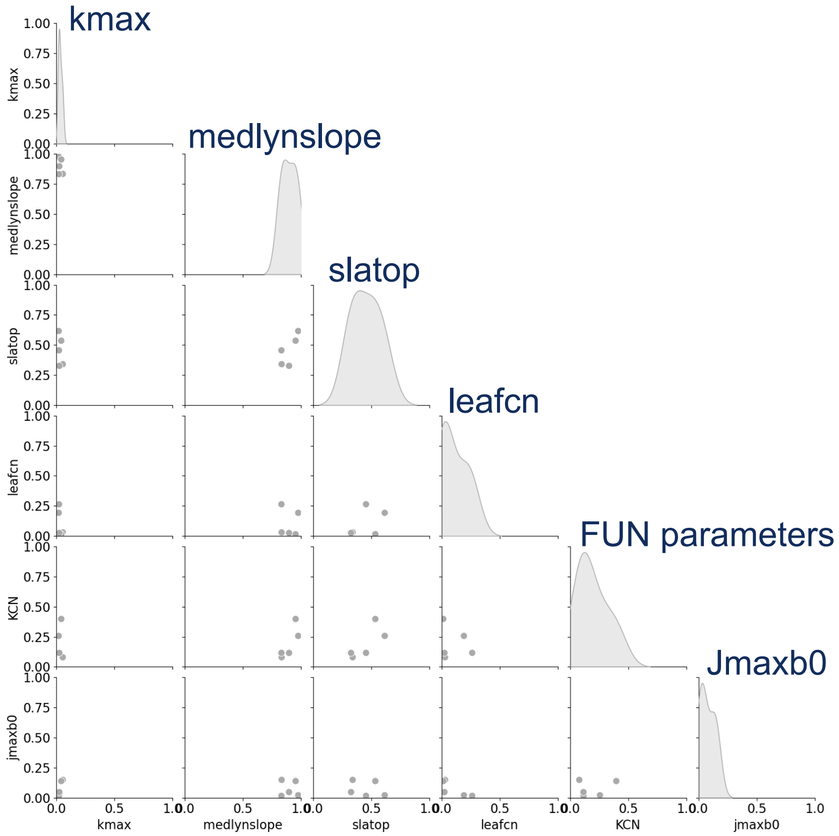
Emulator validation (R^2 score)

	Tropical rainforest	Tropical savanna	Subtropical savanna	Broadleaf evergreen temperate tree	Grasslands	Shrubland	Mixed deciduous temperate forest	Conifer forest	Siberian larch	Boreal forest	Broadleaf deciduous boreal trees	Boreal shrubland	Tundra
LAI	0.98	0.96	0.96	0.95	0.95	0.91	0.96	0.96	0.97	0.97	0.96	0.94	0.95
GPP	0.96	0.95	0.95	0.95	0.93	0.91	0.95	0.95	0.97	0.96	0.93	0.94	0.96
Biomass	0.97	0.97	0.94	0.95	0.93	0.91	0.96	0.96	0.97	0.95	0.94	0.93	0.95

Calibration

Tropical Leaf Area Index





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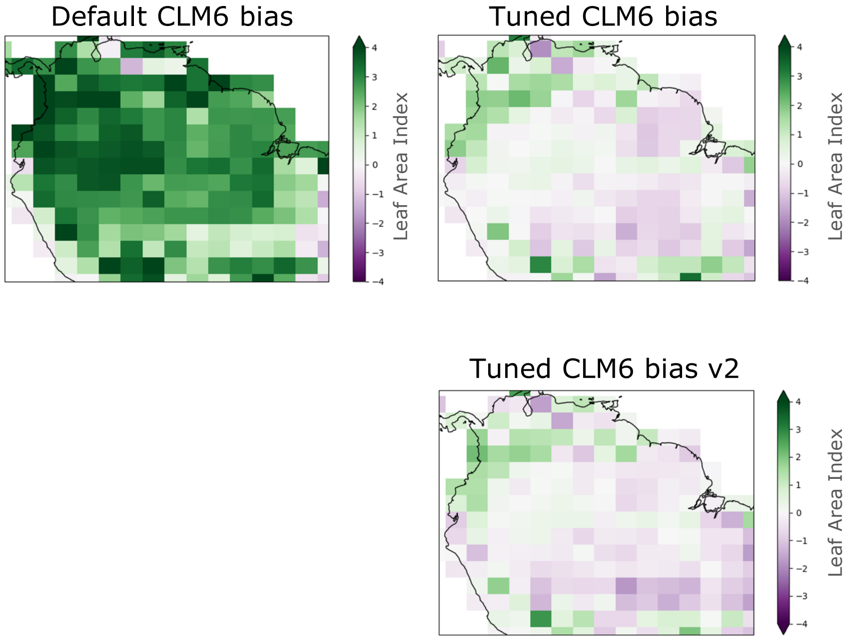
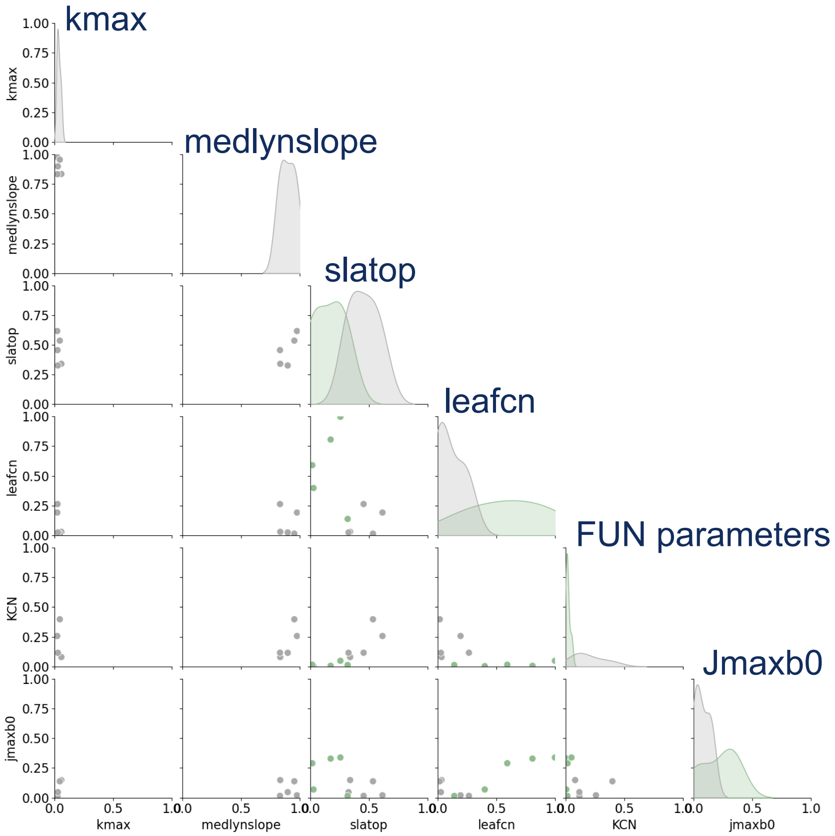
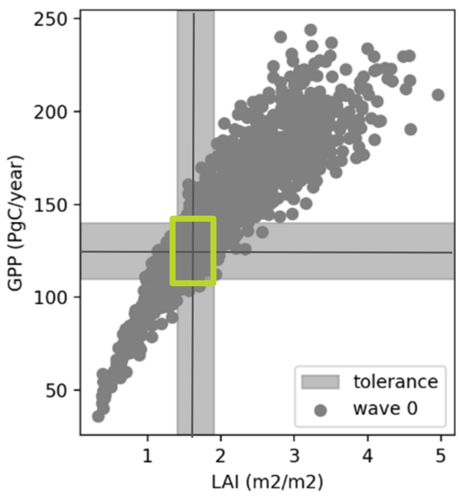




History Matching

- Identifies an ensemble of parameter sets that are in agreement with observations
- Avoids overfitting to limited observations



Constrained PPE

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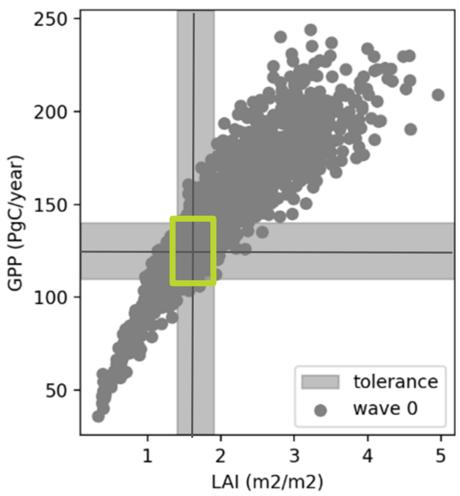
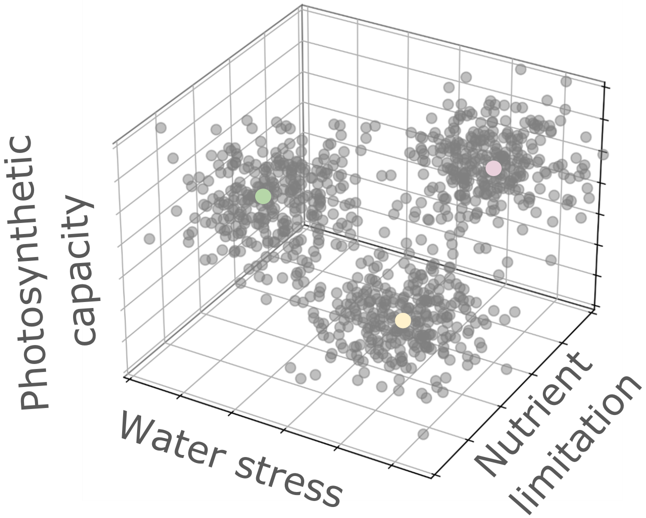
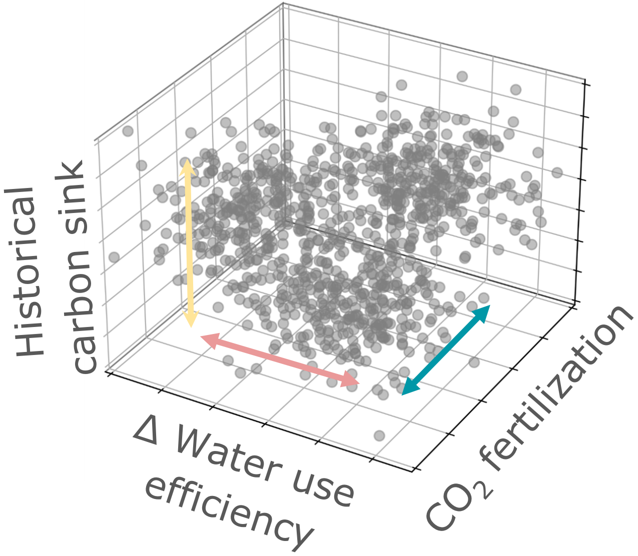


Cluster in parameter space



Uncertainty quantification

- Identify parameter sets that span some emergent behavior
- Assess sources of uncertainty in the projected strength of the land carbon sink
- Emissions driven runs?



How is this going?

Things that are going well:

- Tuning PFT parameter independently
- History matching methodology is very flexible
  - Iteratively introduce constraints

Things that need to be improved:

- Better constraints (water cycle)
- Emulation is too task specific
- Translating offline tuning to coupled model
- Identifying and addressing structural or functional limitations.

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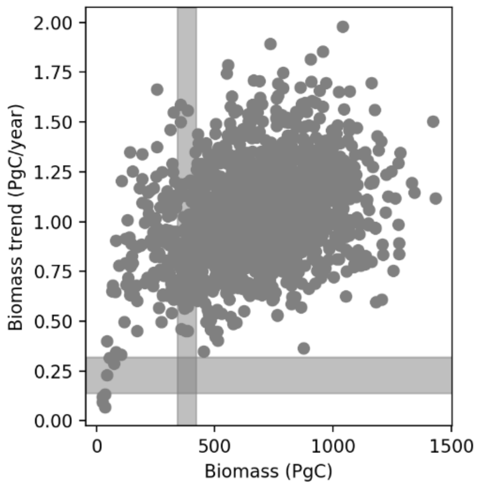
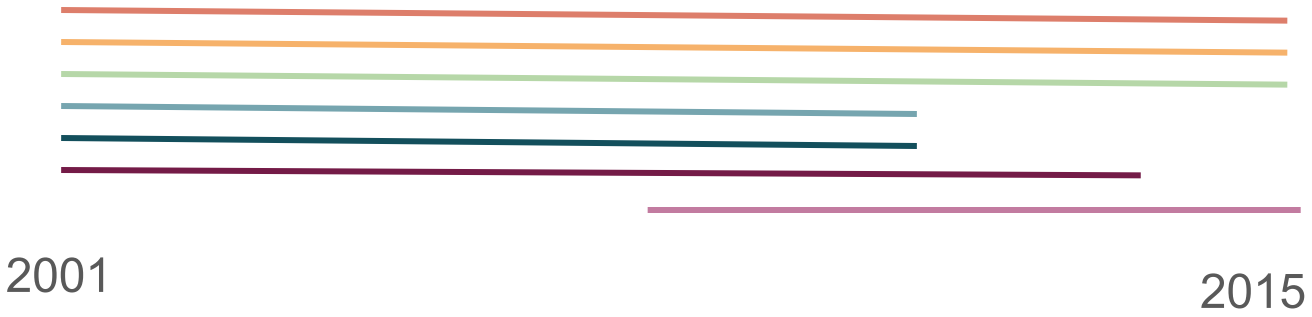


Xu, Saatchi et al., (2021)

Observational mean and stdev

Select range of years that have at least 3 observational products.
Products must have at least 5 years within range



Mean: Sample one product per year. Take the mean. Repeat 10000 times.
Stdev: Standard deviation across products for each year. Averaged.

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