

Towards Flexible Interfacing of Machine Learning with Land Models

David Lawrence
CESM Chief Scientist



Future





LSMS 2022
LAND SURFACE MODELLING SUMMIT

September, 2022

Eleanor Blyth and David Lawrence

***Steering Committee: Aaron Boone, Simon Dadson, Rosie Fisher,
Martin de Kauwe, Julia Pongratz, Kei Yoshimura***

Administrative Support: Victoria Barlow, Marcia Spencer





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Land and Earth System models are increasingly being asked to provide information on societally-relevant impacts and adaptation associated with climate and environmental change

- Ecosystem vulnerability and impacts on carbon cycle and ecosystem services
- Water and food security in context of climate variability, change, and extreme weather
- Land-based mitigation solutions (net-zero targets); Impacts of land use and land-use change on climate, carbon, water, and extremes
- Hazard prediction (drought, floods, fire, heat waves, etc) under a changing climate
- *Understand and exploit sources of predictability from land processes, Earth System prediction*



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EDITORIAL | 16 August 2022

We must get a grip on forest science – before it's too late

Trees are one of our biggest carbon hopes. Supporting the scientists studying them should be a much higher priority.

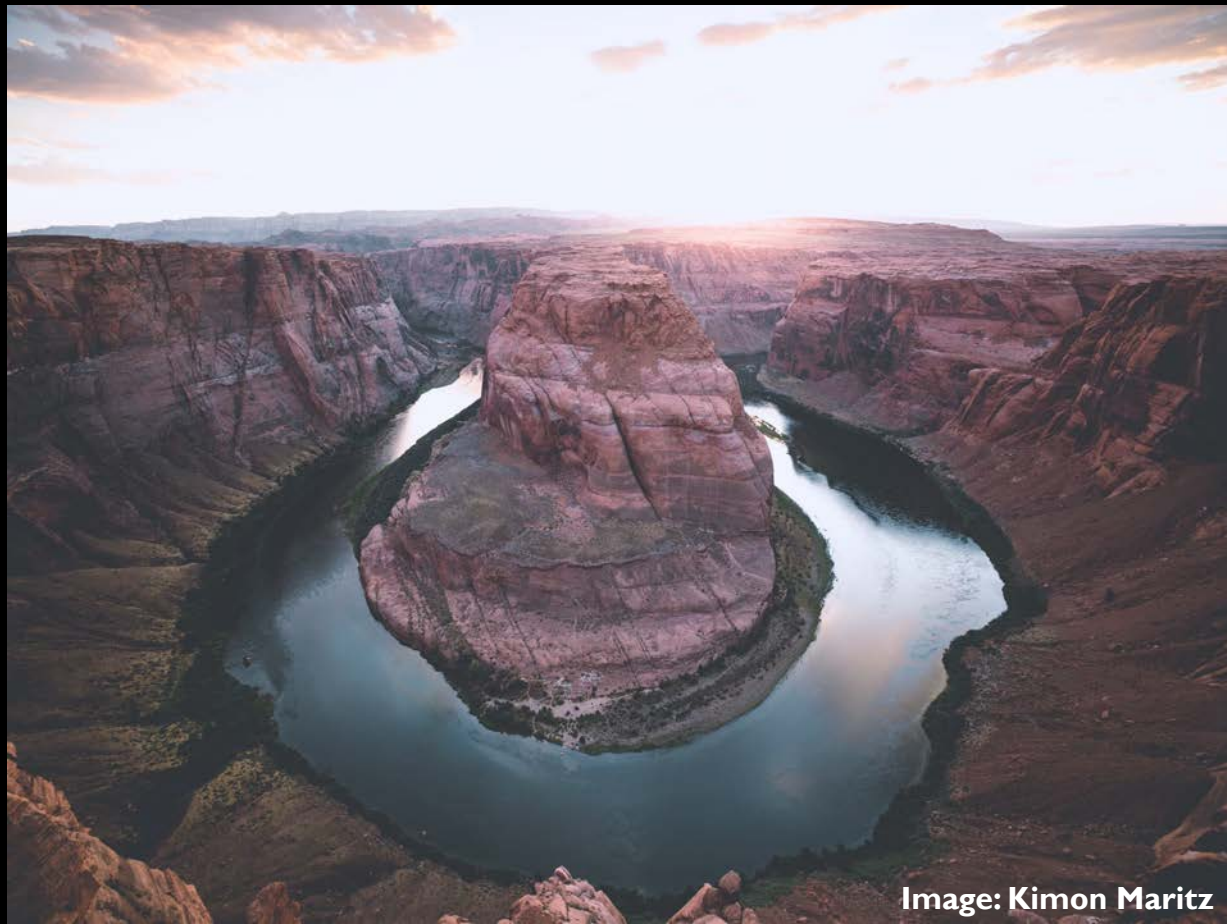


Image: Kimon Maritz

**Will we have
enough
water?**



**Will we be able to
produce enough food?**





Where and when will people and ecosystems experience more extreme events?





Where are we going to put the carbon (and will it stay there)?



Perspectives on the Future of Land Surface Models and the Challenges of Representing Complex Terrestrial Systems

Rosie A. Fisher, Charles D. Koven 

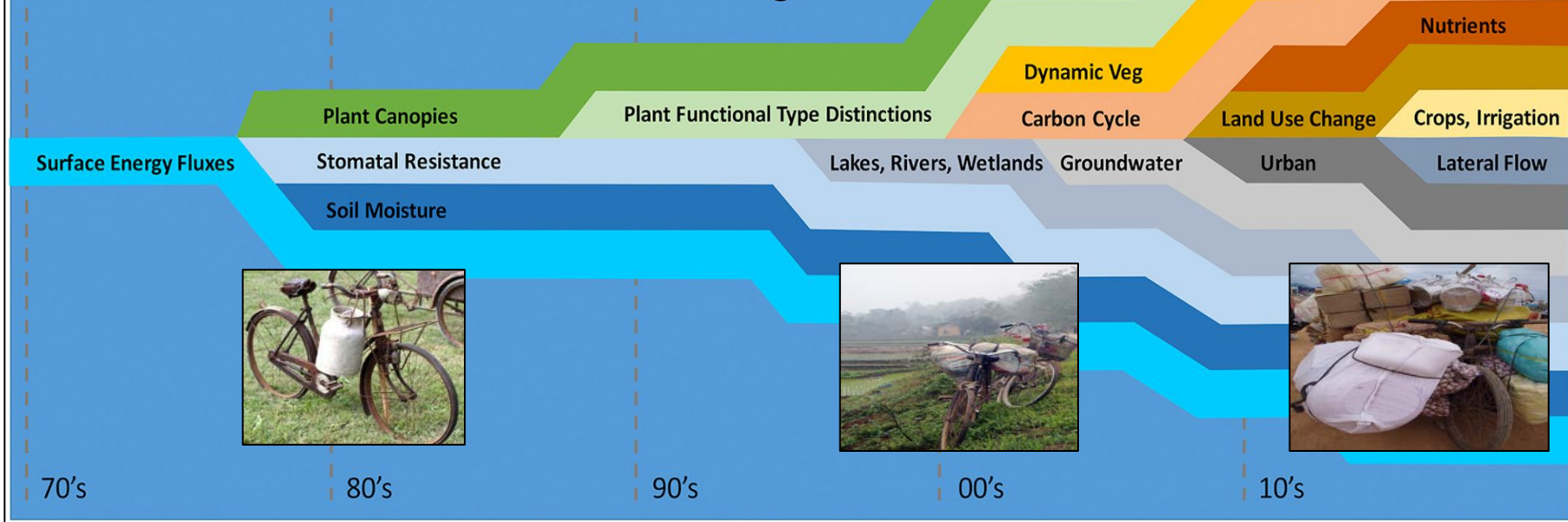
First published: 10 March 2020 | <https://doi.org/10.1029/2018MS001453> | Citations: 79

Advances in Land Surface Modelling

[Eleanor M. Blyth](#) , [Vivek K. Arora](#), [Douglas B. Clark](#), [Simon J. Dadson](#), [Martin G. De Kauwe](#),
[David M. Lawrence](#), [Joe R. Melton](#), [Julia Pongratz](#), [Rachael H. Turton](#), [Kei Yoshimura](#) & [Hua
Yuan](#)

Current Climate Change Reports 7, 45–71 (2021) | [Cite this article](#)

The Evolution of Land Surface Modeling



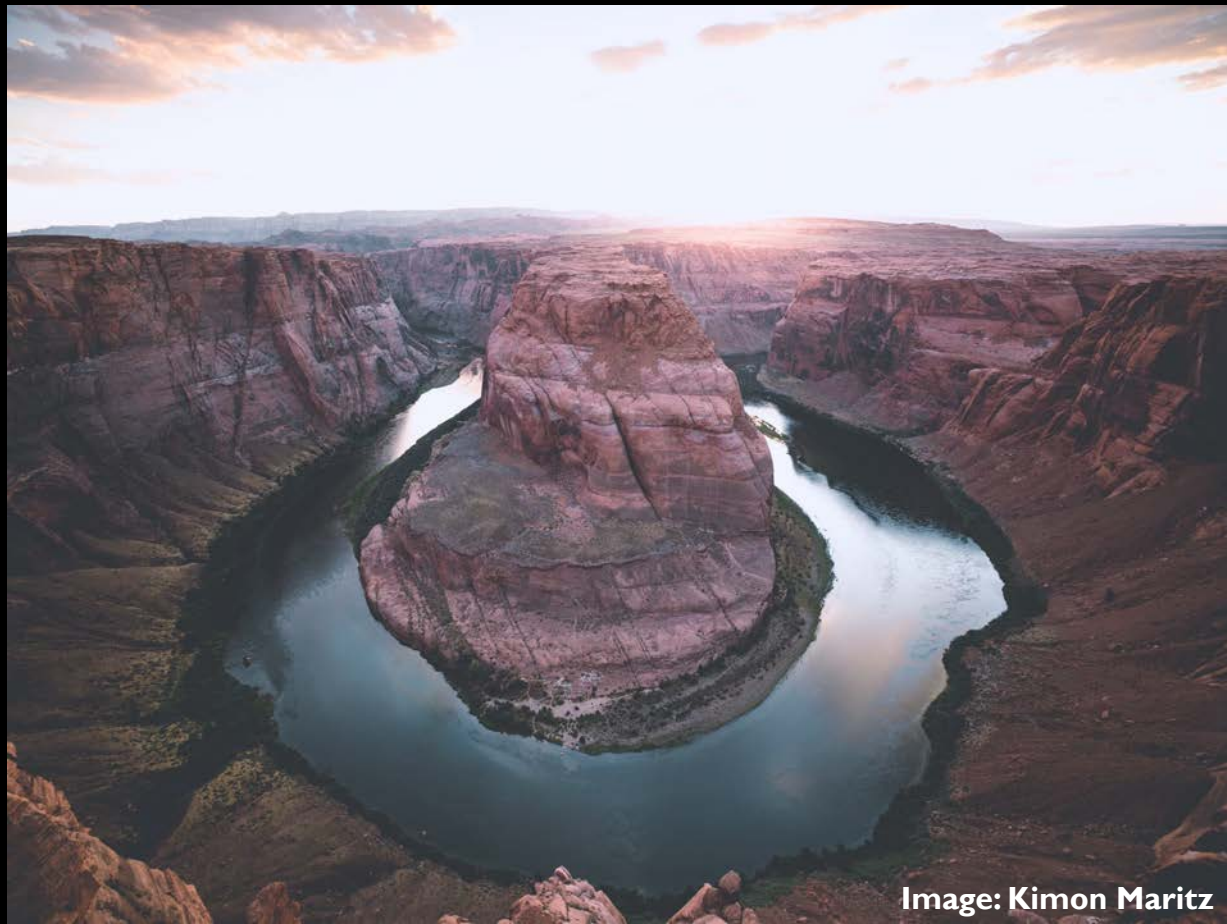
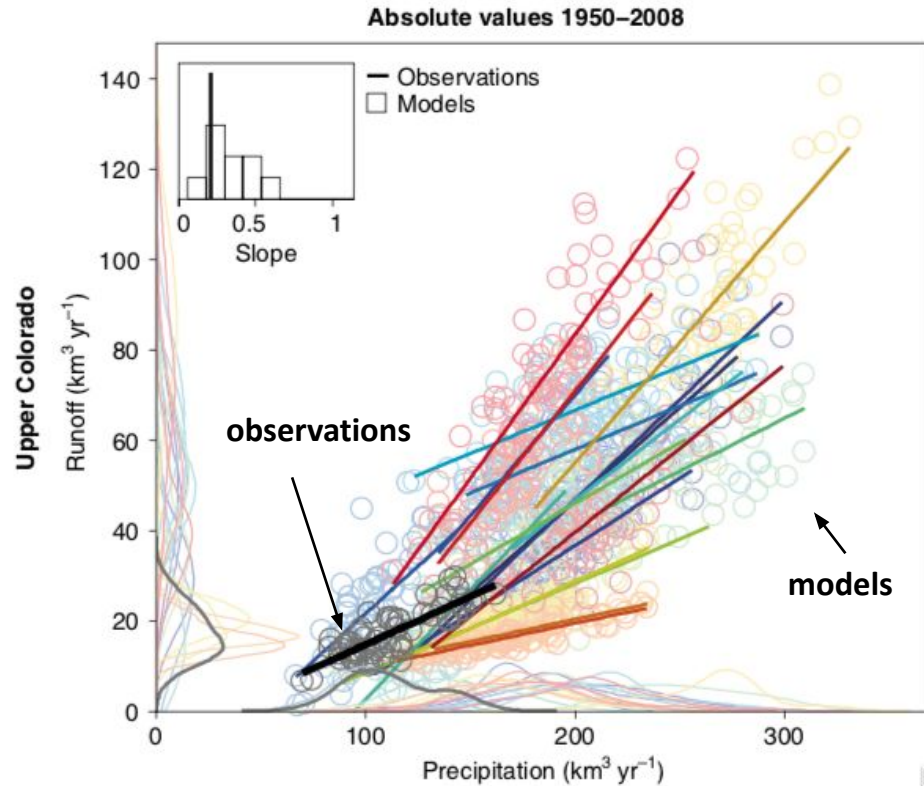


Image: Kimon Maritz

**Will we have
enough
water?**

Example actionable science limitation: ESMs do not accurately simulate hydrologic sensitivity



CMIP models do not accurately represent changes in runoff associated with changes in P or T, which limits usability of runoff projections for adaptation purposes

PERSPECTIVE

<https://doi.org/10.1038/s41558-019-0639-x>

nature
climate change

The potential to reduce uncertainty in regional runoff projections from climate models

Flavio Lehner^{1,2,3*}, Andrew W. Wood², Julie A. Vano^{2,4}, David M. Lawrence¹, Martyn P. Clark⁴ and Justin S. Mankin^{4,2,8}



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LAND SURFACE MODELLING SUMMIT

Goal of the summit was to identify collaborative steps or activities that could be taken to **accelerate progress**

Focal Sessions

- New approaches for subgrid heterogeneity
- Managing model complexity
- Towards sharing of modules across LSMs
- Input and forcing datasets
- Crop modeling and forestry
- Water and land management
- Coupling external models to LSMs
- Fire and humans
- Land model benchmarking
- Machine learning approaches and LSMs
- Parameter estimation and uncertainty



LSMS 2022

LAND SURFACE MODELLING SUMMIT



Recordings of presentations available from the conference webpage

<https://hydro-jules.org/lsm2022-resources>



Goals of the Summit

Formal

- Collectively create a Road Map to address the challenges to improve land models so that they are fit for purpose to address scientific and societal needs associated with anthropogenically and naturally-driven environmental change
- Develop plans for follow up meetings and working groups, which can be used as basis for modeling groups and collaborative partners to solicit funding to support development activities and to build a community effort to accelerate progress

Informal

- Develop a shared understanding of the 'pain points' in modern land model development and application
- Foster collaborative relationships to address these challenges



Climate science is in transition



Urgent needs:

- **actionable information (climate risks under different emissions scenarios; consequences of intervention/mitigation)**
- **more robust understanding of risks of tipping points**

Yet, progress towards more accurate and reliable Earth System models remains slow

Next-generation Earth System modeling to address urgent mitigation and adaptation needs

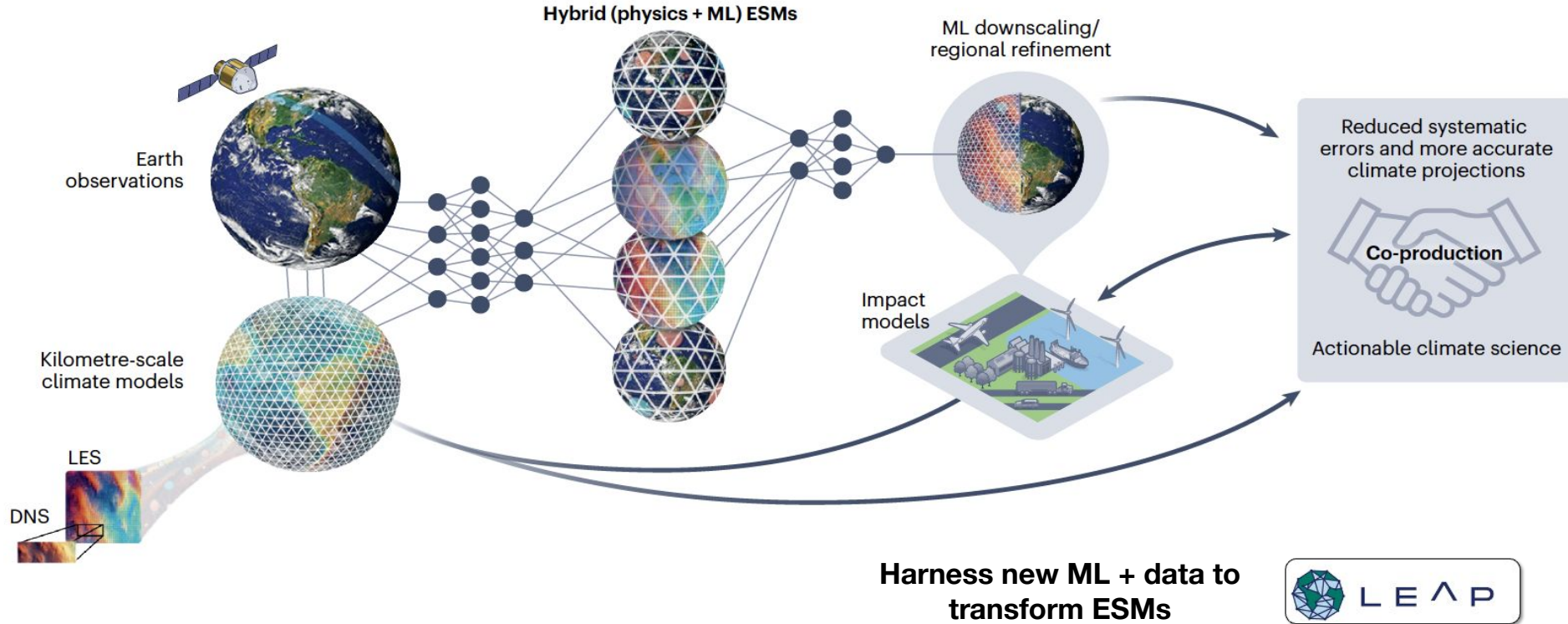


Figure from Eyring, Gentine, Camps-Valls, Lawrence, Reichstein (Nature Climate Change, 2024)

*LEAP forward in the **reliability**, **utility**, and **reach** of climate projections through synergistic innovations in data science and climate science*

Next-generation Earth System modeling to address urgent mitigation and adaptation needs

So, what is needed to realize and accelerate the potential of ML to improve land modeling?

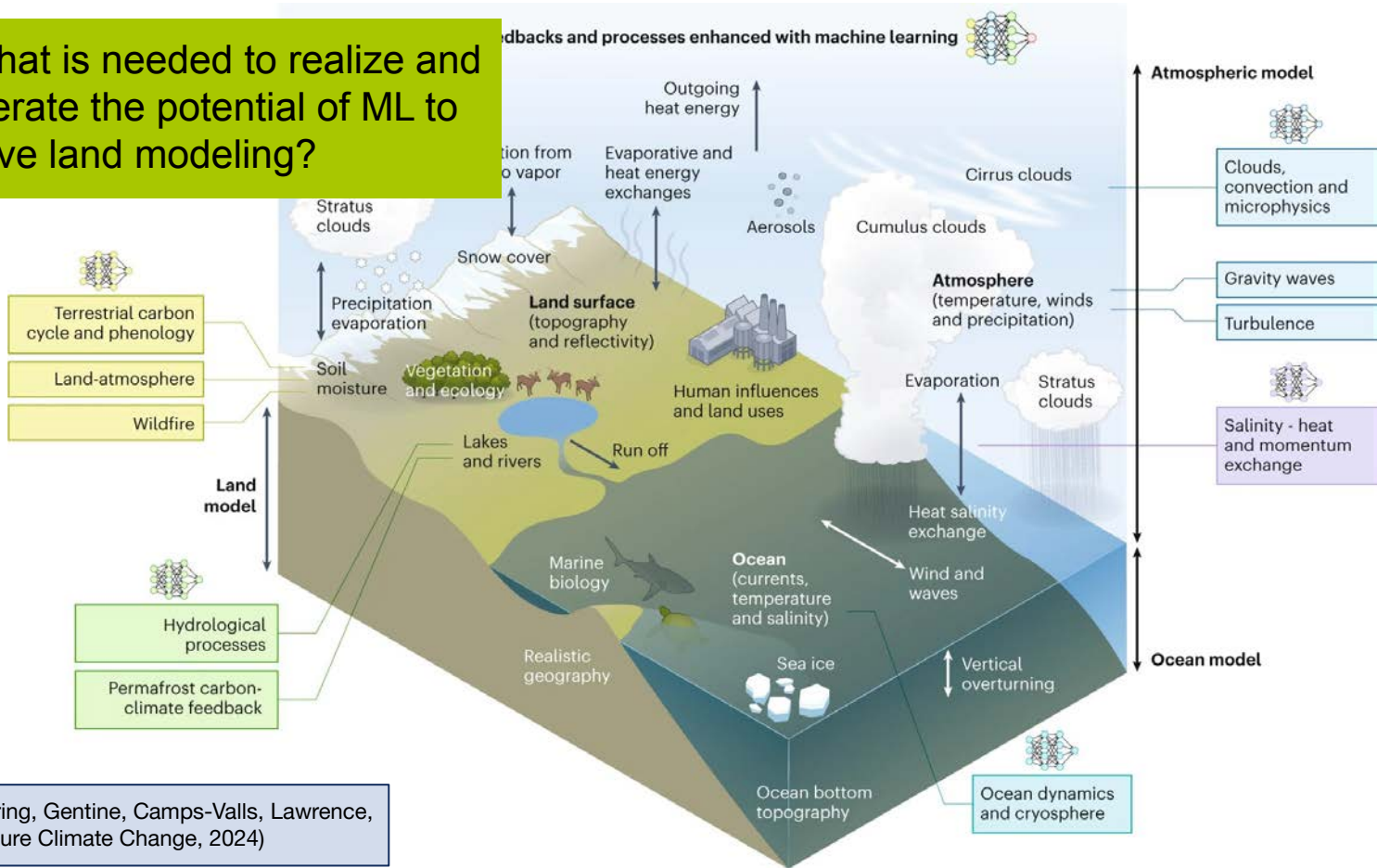


Figure from Eyring, Gentine, Camps-Valls, Lawrence, Reichstein (Nature Climate Change, 2024)

International Land Modelling Forum (ILMF)

The ILMF emerged from the Land Surface Modelling Summit in Oxford in Sept 2022. It provides a forum through which land modelling centres and researchers can interact and collaborate on mutually beneficial projects by

- **sharing ideas**
- **promoting relevant workshops and meetings**
- **advertising job opportunities**
- **coordinating working groups**

Initial working groups will focus on shareable modules, parameter estimation, the challenges of integrating humans into ESMs, and benchmarking.



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ILMF
INTERNATIONAL LAND MODELING FORUM

To join the ILMF, goto
<https://rebrand.ly/ILMF>

**International Land Modelling Forum
(ILMF) Interactive Webinars**
September – October 2023



Available at
<https://hydro-jules.org/international-land-modeling-forum-ilmf>



Code Refactoring

Before

some_subroutine

```
calc. flux 1  
...  
...  
...  
update state 1  
calc. flux 2  
...  
...  
...  
calc. flux 3  
...  
...  
...  
update state 2
```

Livable Code

<https://brightonruby.com/2017/livable-code-sarah-mei/>



Slide credit Bill Sacks

You have to live here

Livable Code

<https://brightonruby.com/2017/livable-code-sarah-mei/>



You **GET** to live here

Pathways Towards Shareable Modules for Land Models

What do we mean by modularity?

Martyn P. Clark, PhD

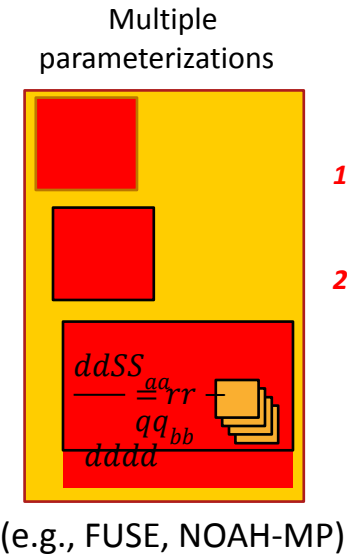
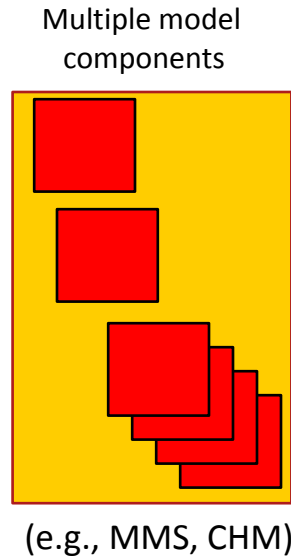
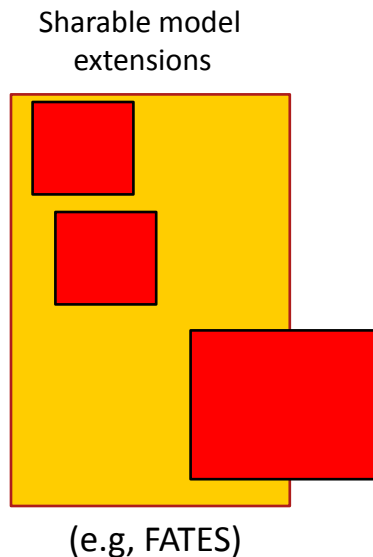
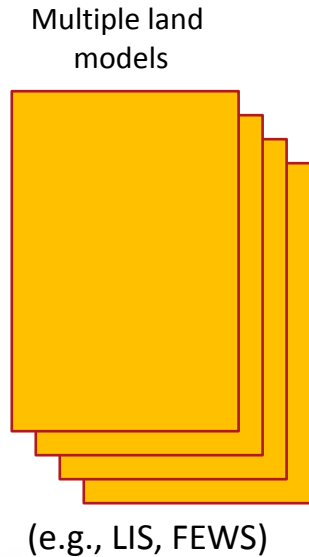
Professor of Hydrology and Schulich Chair for Environmental Prediction

Department of Civil Engineering, Schulich School of Engineering, University of
Calgary

21 September 2023

Unifying model physics

- **The problem:** A glut of hydrological models (Clark et al., WRR 2011) – in many cases there are more models in use than there are algorithms to populate them (same algorithms across multiple models)
- **The challenge:** Can we define a general “master modeling template” (general design principles) from which existing models can be constructed and new models derived (Clark et al., WRR 2015)?
- **The challenge:** Can we unify model building blocks across multiple levels of granularity?



How do you thread the needle between:

1. **Multiple models** that work together in the same framework; and
2. **Multiple parameterizations** that work together in a plug-and-play environment

increasing levels of granularity



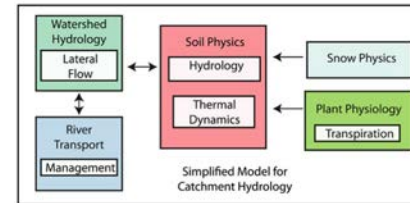
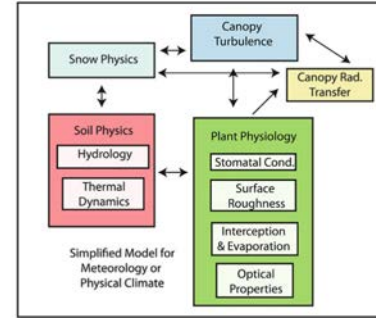
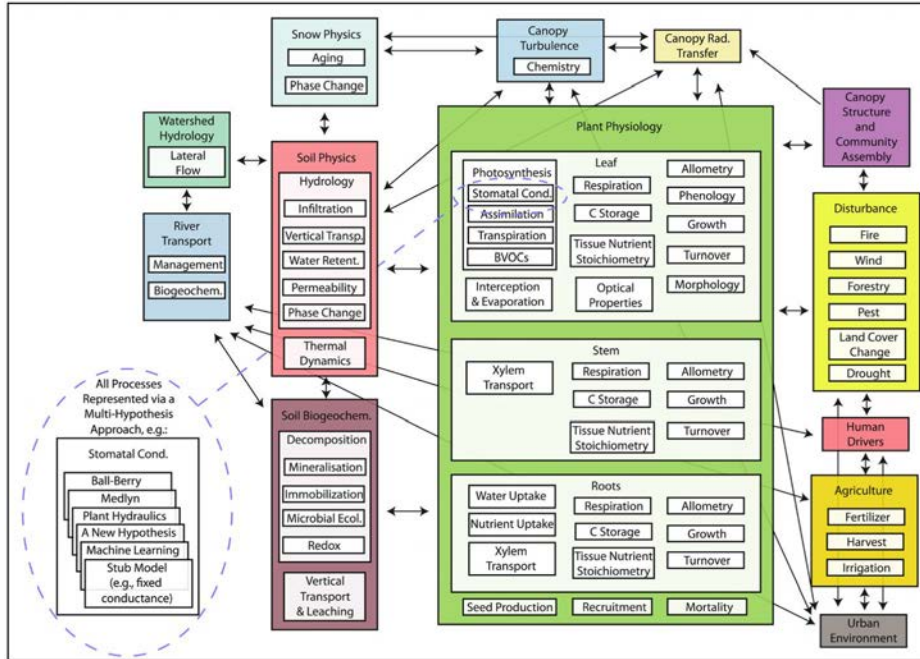


The Functionally Assembled Terrestrial Ecosystem Simulator (FATES): Modularity, Configurability, and Interoperability

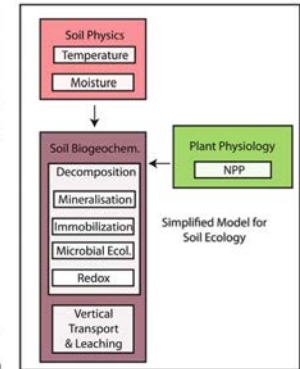
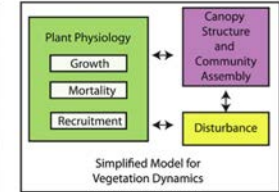
C. Koven, R. Fisher, R. Knox,
B. Christoffersen, Y. Fang, A. Foster, J. Holm, E. Kluzek, L. Kueppers, D. Lawrence, G. Lemieux, S. Levis, M.
Longo, J. Needham, W. Sacks, J. Shuman, M. Vertenstein, A. Walker, W. Wieder, C. Xu, and many others



Process-level modularity vs configurability (We have focused on both with FATES)

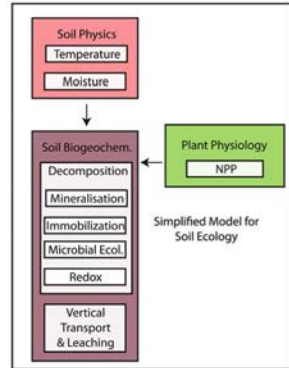
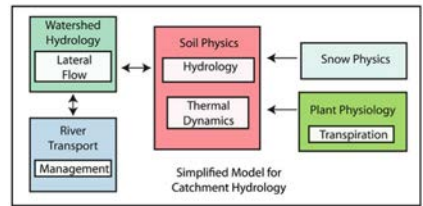
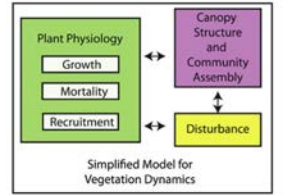
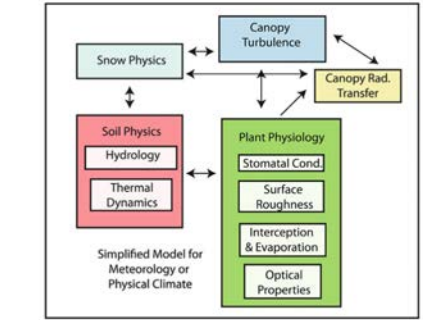
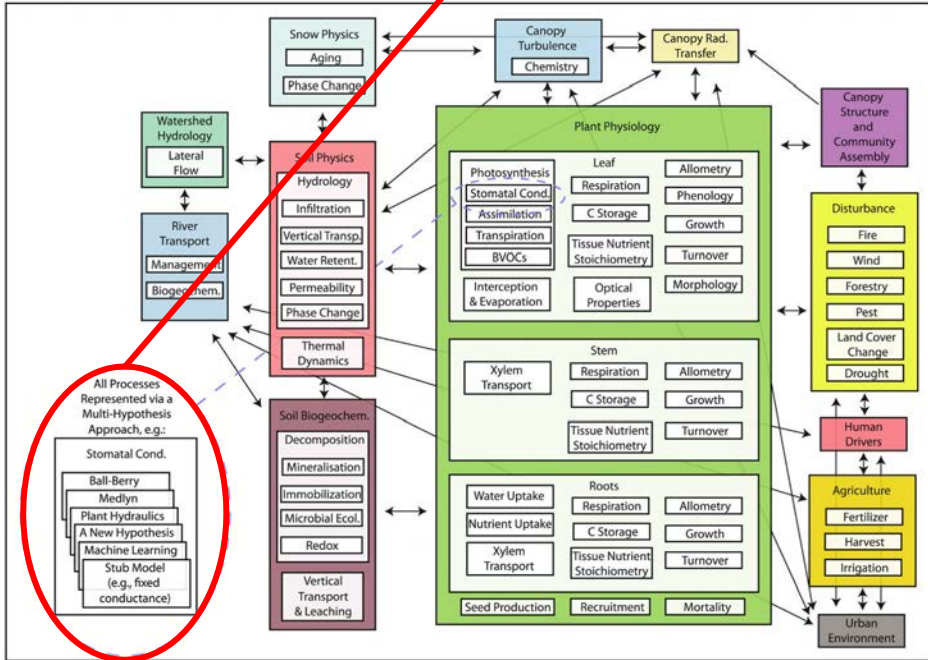


(b) Some Possible Simplified Configurations of a Land Surface Model



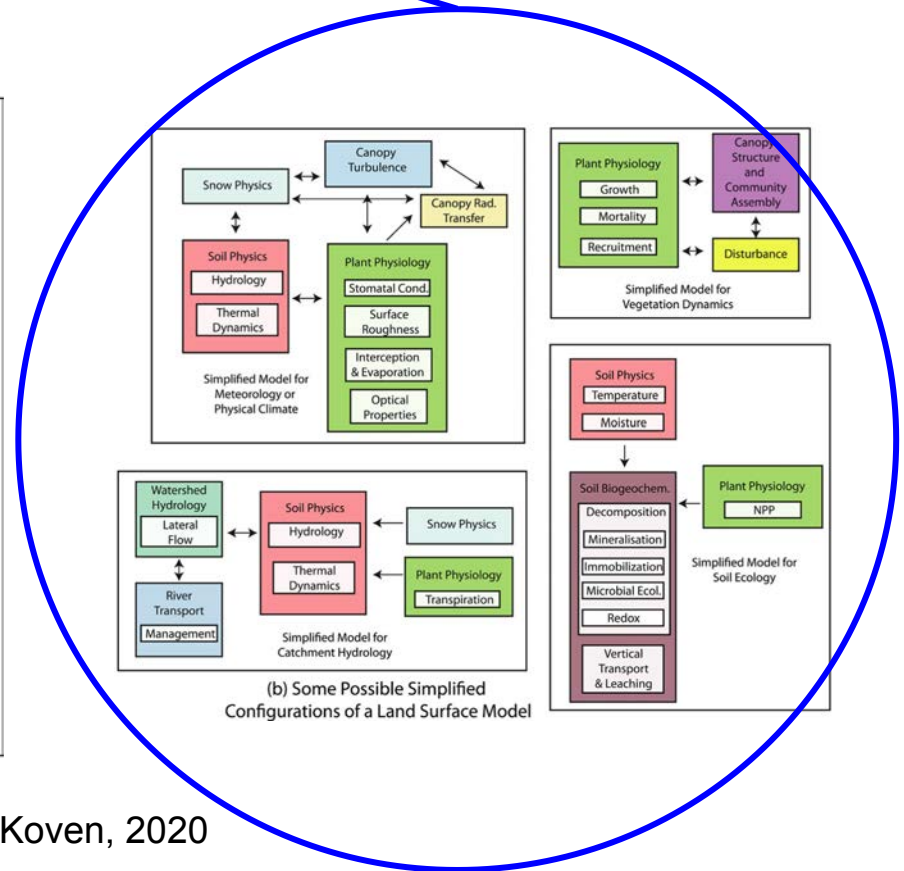
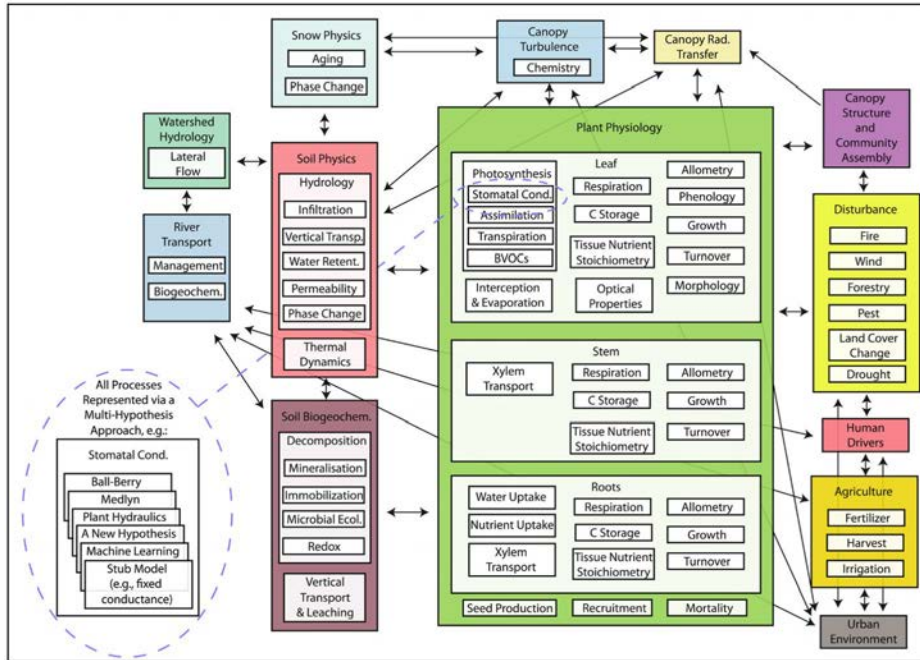
Process-level modularity vs configurability

(We have focused on both with FATES)



(b) Some Possible Simplified Configurations of a Land Surface Model

Process-level modularity vs configurability (We have focused on both with FATES)



Modularisation in Land Surface models: discussion & future steps

Martyn Clark, Philippe Peylin, Dave Lawrence, Eleanor Blyth, Simon Dadson, Charlie Koven, Dai Yamazaki,...

Two possible paths for international collaboration ...

Global LSM



High level components

(ex. CamaFlood, FATES,...)

Intermediate level: groups of processes

(ex. Snow dynamic, Leaf level photosynthesis, Soil C dyn., ...)

Low level: Individual processes

(ex. process descriptions...)

Individual processes

Approach 1 “Top - down”

*Define generic
“Modules” with
standard
interfaces*

*Start with a
concrete
example (ex.
Leaf phenology,
SOM decomp.,...*

Approach 2 “bottom up”

Building blocks towards a hybrid Earth System Model



Building blocks towards a hybrid Earth System Model



Robust and flexible Implementation of ML-based parameterizations requires Fortran-Python bridge

- FTorch implementation with CESM working fairly well
- To enable broad use, needs an integration plan to bring fully into CESM3 infrastructure
- Documentation for users
- Robust testing, edge-case evaluation
- GPU-CPU combo testing
- Ideally, some consistency in implementation of Fortran-Python bridge across modeling centers



The Community Land Model (CLM5) Parameter Perturbation Experiment

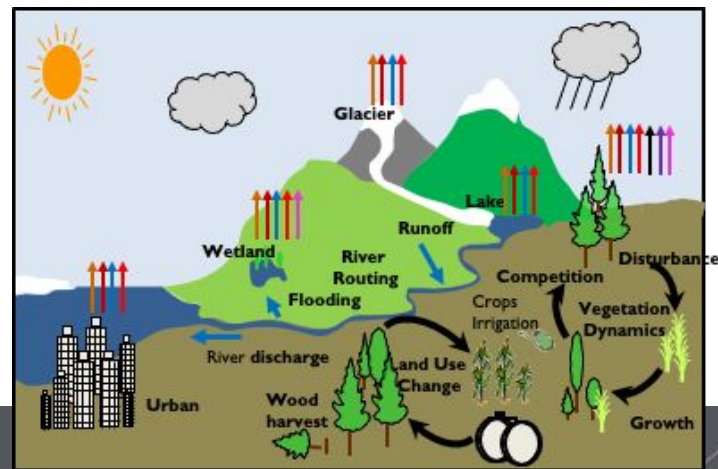
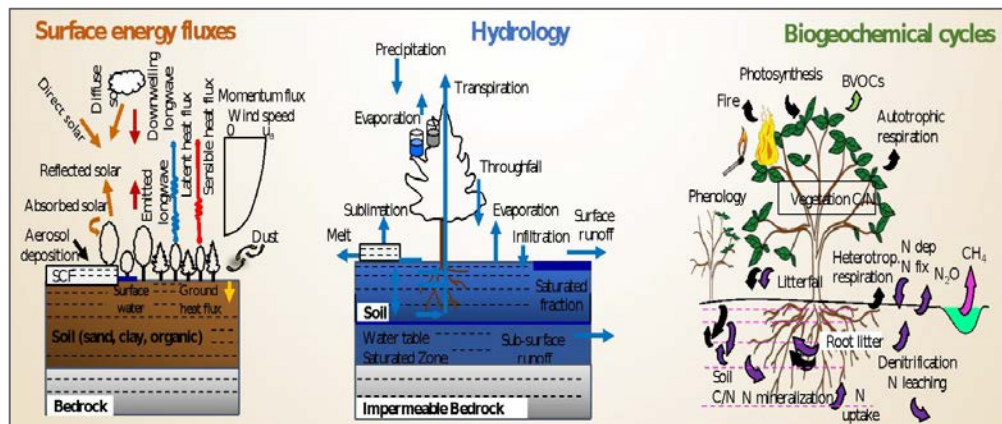
Quantifying parametric uncertainty and working towards automated calibration

Linnia Hawkins, Daniel Kennedy, Katie Dagon



Motivation for the CLM PPE Project

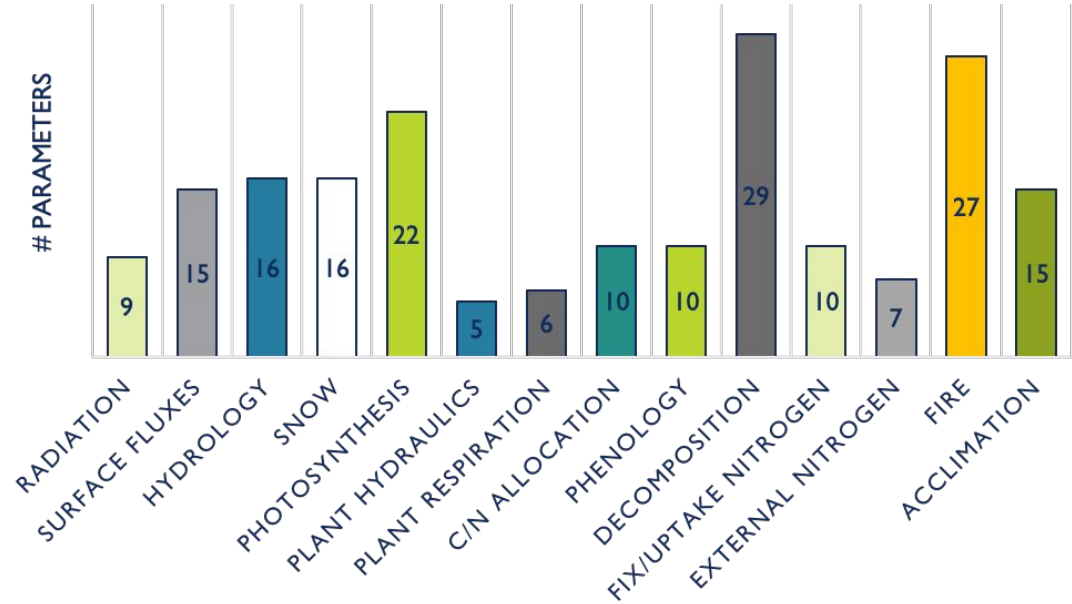
- Growing complexity and comprehensiveness of land models → increasing # of uncertain parameters



Motivation for the CLM PPE Project

- Growing complexity and comprehensiveness of land models → increasing # of uncertain parameters

CLM5(BGC) has over 200 parameters



Motivation for the CLM PPE Project

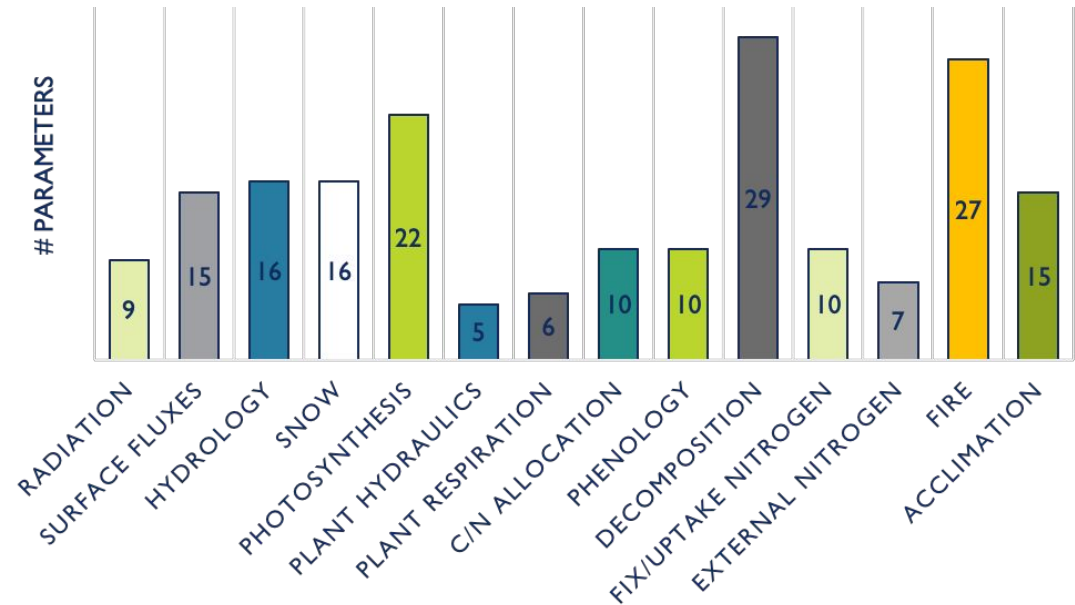
- Growing complexity and comprehensiveness of land models → increasing # of uncertain parameters

Drawbacks of hand tuning

- Difficult to diagnose structural improvements
- Challenging to incorporate new parameterizations
- Impractical requisite knowledge base
- Doesn't scale well with increasing complexity

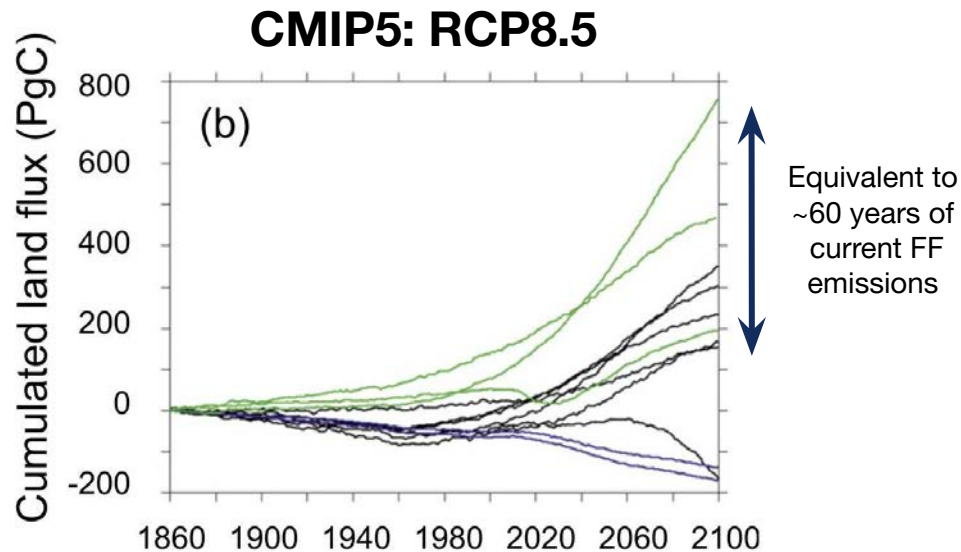


CLM5(BGC) has over 200 parameters



Motivation for the CLM PPE Project

- Growing complexity and comprehensiveness of land models → increasing # of uncertain parameters
- Contribution of parameter uncertainty to total uncertainty expected to be large, but largely unquantified



Emissions driven RCP8.5: 795 to 1140 ppm CO₂
→ ±1.2C uncertainty on top of 3.7C projected change

Motivation for the CLM PPE Project

- Growing complexity and comprehensiveness of land models → increasing # of uncertain parameters
- Contribution of parameter uncertainty to total uncertainty expected to be large, but largely unquantified
- Systematic parameter calibration will enhance accuracy of simulations, and increase suitability and accessibility of CLM for actionable science

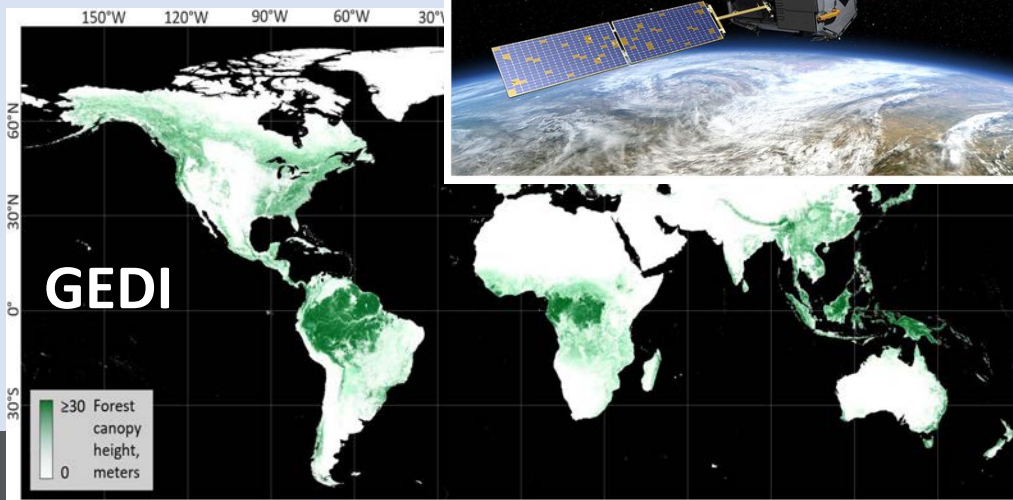


- Ecosystem vulnerability and impacts on carbon cycle and ecosystem services
- Water and food security in context of climate change, climate variability, and extreme weather
- Ecological, hydrological, and Earth system prediction
- Terrestrial contribution to Net Zero emissions goals

Unprecedented availability of Earth Observations



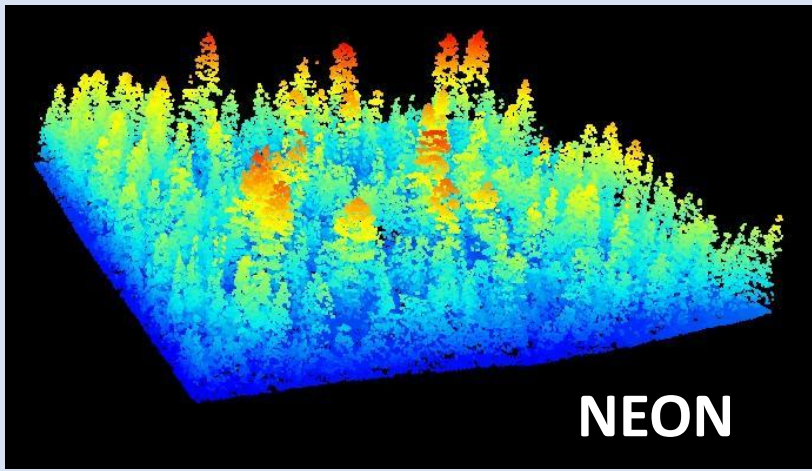
Unprecedented availability of Earth Observations



Unprecedented availability of Earth Observations



Flux tower networks like NEON, Ameriflux, FluxNet



And new integrated metrics packages

CMIP6

	BCC-CSM2-MR	CanESM5	CESM2	CNRM-ESM2-1	E3SM-CTC	E3SM-ECA	EC-Earth3-Veg	GFDL-CM4	GISS-E2-1-G	IPSL-CM6A-LR	MIROC-ES2L	NorESM2-LM	UKESM1-0-LL	MeanCMIP6
Ecosystem and Carbon Cycle														
Biomass														
Burned Area														
Carbon Dioxide														
Gross Primary Productivity														
Leaf Area Index														
Global Net Ecosystem Carbon Balance														
Net Ecosystem Exchange														
Ecosystem Respiration														
Soil Carbon														
Hydrology Cycle														
Evapotranspiration														
Evaporative Fraction														
Latent Heat														
Runoff														
Sensible Heat														
Terrestrial Water Storage Anomaly														
Permafrost														
Radiation and Energy Cycle														
Forcings														
Surface Air Temperature														
Diurnal Max Temperature														
Diurnal Min Temperature														
Diurnal Temperature Range														
Precipitation														
Surface Relative Humidity														
Surface Downward SW Radiation														
Surface Downward LW Radiation														
Relationships														
BurnedArea/GFED4S														
GrossPrimaryProductivity/GBAF														
LeafAreaIndex/AVHRR														
LeafAreaIndex/MODIS														
Evapotranspiration/GLEAM														
Evapotranspiration/MODIS														

International Land Model Benchmarking (ILAMB) project

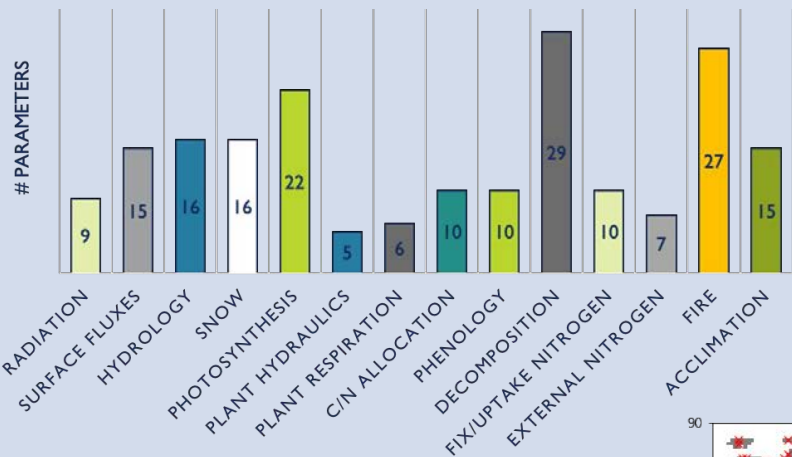
- Integrates analysis of ~35 land variables against 90+ global, regional, and site-level observational datasets
- Graphics and scoring system for
 - RMSE
 - bias
 - seasonal cycle phase
 - spatial patterns
 - interannual variability
 - variable-to-variable relationships

DOE, NCAR, University collaboration

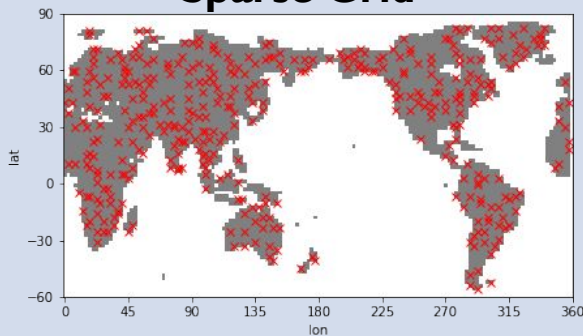


CLM PPE Project

- **Phase 0:** Infrastructure development (fast spinup, expose parameters, identify parameter ranges, ensemble and analysis scripting)



Sparse Grid



Until recently, computationally prohibitive to attempt to calibrate global CLM(BGC)

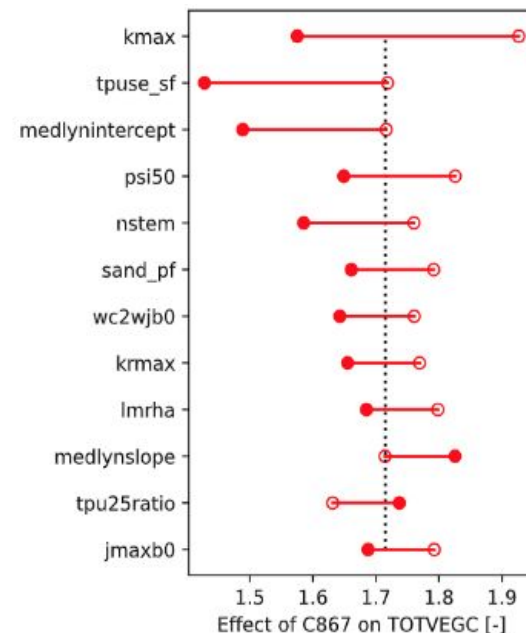
- Cluster analysis → reasonably replicate global simulation results with 400 gridcells (Hoffman et al., 2013)
- Matrix solution to C/N initial states decreases spinup timescale by >10X (Lu et al., 2020)

CLM PPE Project

- **Phase 0:** Infrastructure development (fast spinup, expose parameters, identify parameter ranges, ensemble and analysis scripting)
- **Phase I:** One-at-a-time parameter ensembles under range of environmental perturbations
 - Control: present-day climate and CO₂
 - Climate: **I850** and **SSP3-7** CESM2 climate
 - CO₂: **I850** and **SSP3-7**
 - N-dep: **+5 gN/m2/yr**
 - *Last Glacial Maximum conditions*
 - Restrict parameter ranges again if **low-side** environmental perturbation doesn't pass reasonableness checks



Top 12 params regulating CO₂ fertilization effect on global vegetation carbon



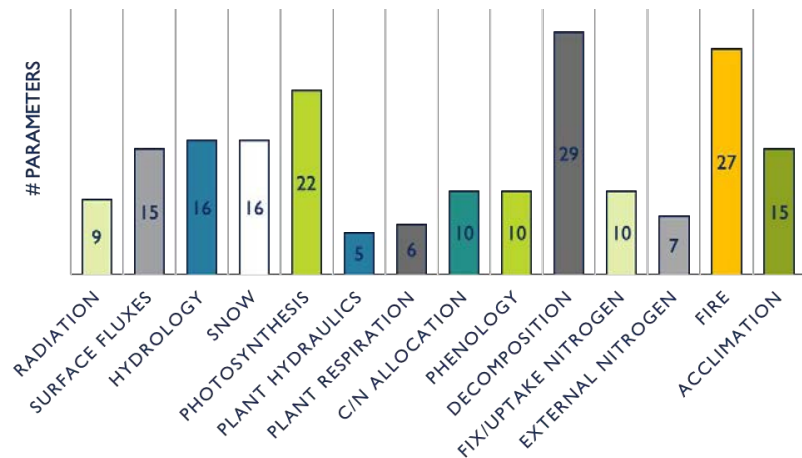
CLM5 Perturbed Parameter Ensemble Project

- **Phase 0:** Infrastructure development (fast spinup, expose parameters, identify parameter ranges, ensemble and analysis scripting)
- **Phase 1:** One-at-a-time parameter ensembles under range of environmental perturbations (low/high CO₂, PI and future climate, N-dep)

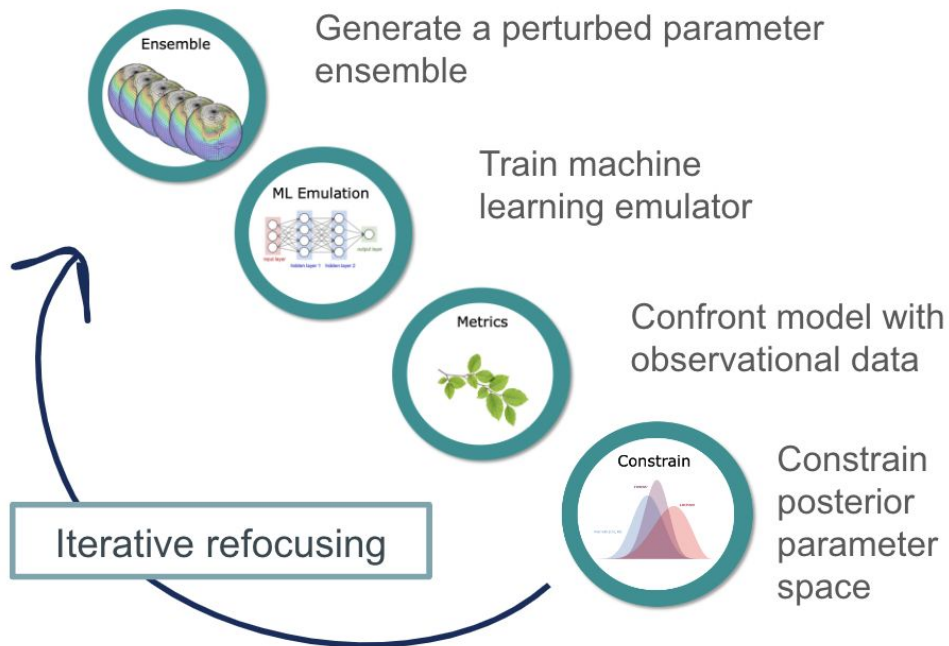
CLM PPE Spinoff Projects

- Land-atmosphere interactions (Univ Washington)
- NEON site calibration (Auburn Univ)
- ET recession timescales (Oregon State)
- Arctic river flow (RAL)
- Land influence on drought (CGD)
- Hydrologic sensitivity (Cornell Univ)
- Tropical carbon cycle interannual variability (JPL)
- GPP response to permafrost thaw (Northern Arizona U)
- ...

CLM5 has over 200 parameters



Towards global parameter calibration (testing with LAI calibration)



Important params for Leaf Area Index

Parameter	Param type
jmaxb0	Photosynthesis
jmaxb1	
wc2wjb0	
theta_cj	
leafcn (PFT)	
jmaxha	Soil hydrology
tpu25ratio	
hksat_sf	
fff	
sucsat_sf	
d_max	Plant water use
kmax (PFT)	
medlynslope (PFT)	
medlynintercept (PFT)	
crit_dayl	
soilpsi_off	
leaf_long (PFT)	Leaf physiology
slatop (PFT)	
lmr_intercept_atkin	Respiration
lmrha	
froot_leaf (PFT)	Allocation
FUN_fracfixers (PFT)	
pc	Snow

History Matching

Train emulator for each PFT

X

y

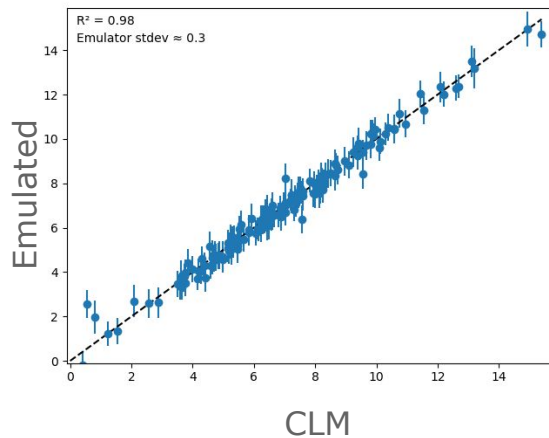
Input parameters
1500 sims x 56 params

P
FT

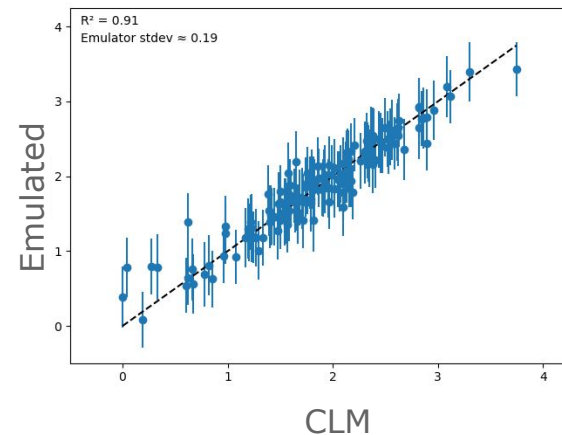
L
A
I

Leaf Area Index

Broadleaf Evergreen
Tropical Tree



Broadleaf Deciduous
Boreal Shrub Tree

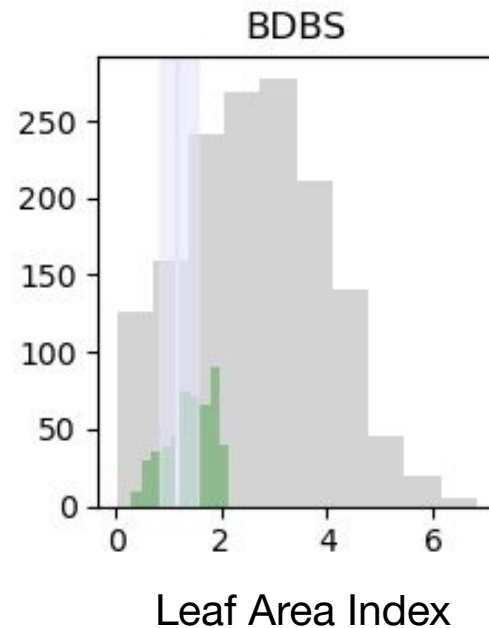
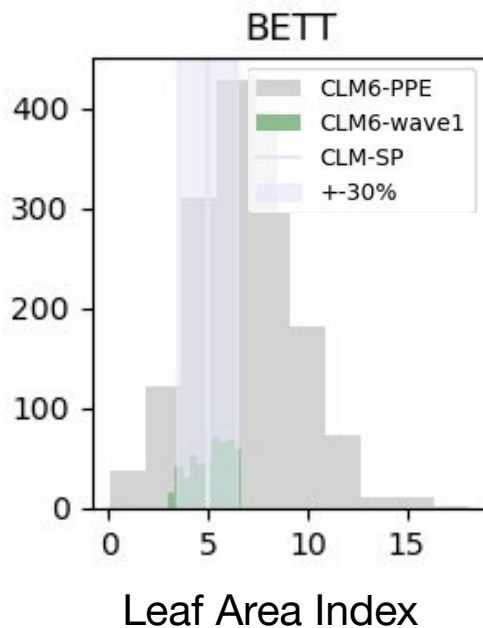


History Matching

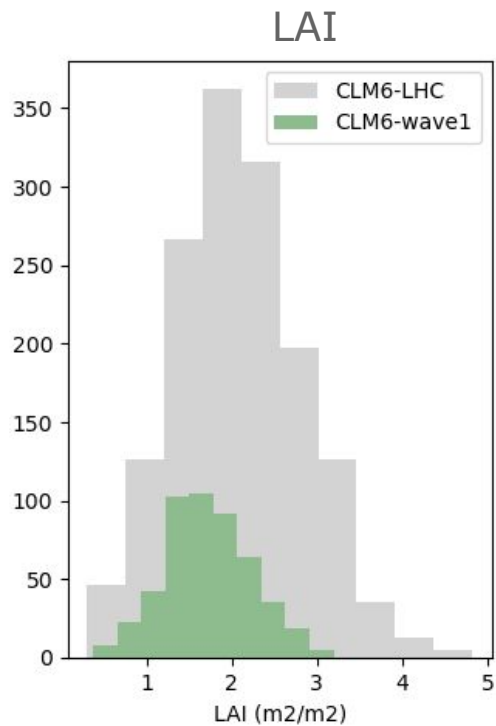
Train emulator for each PFT

History Matching

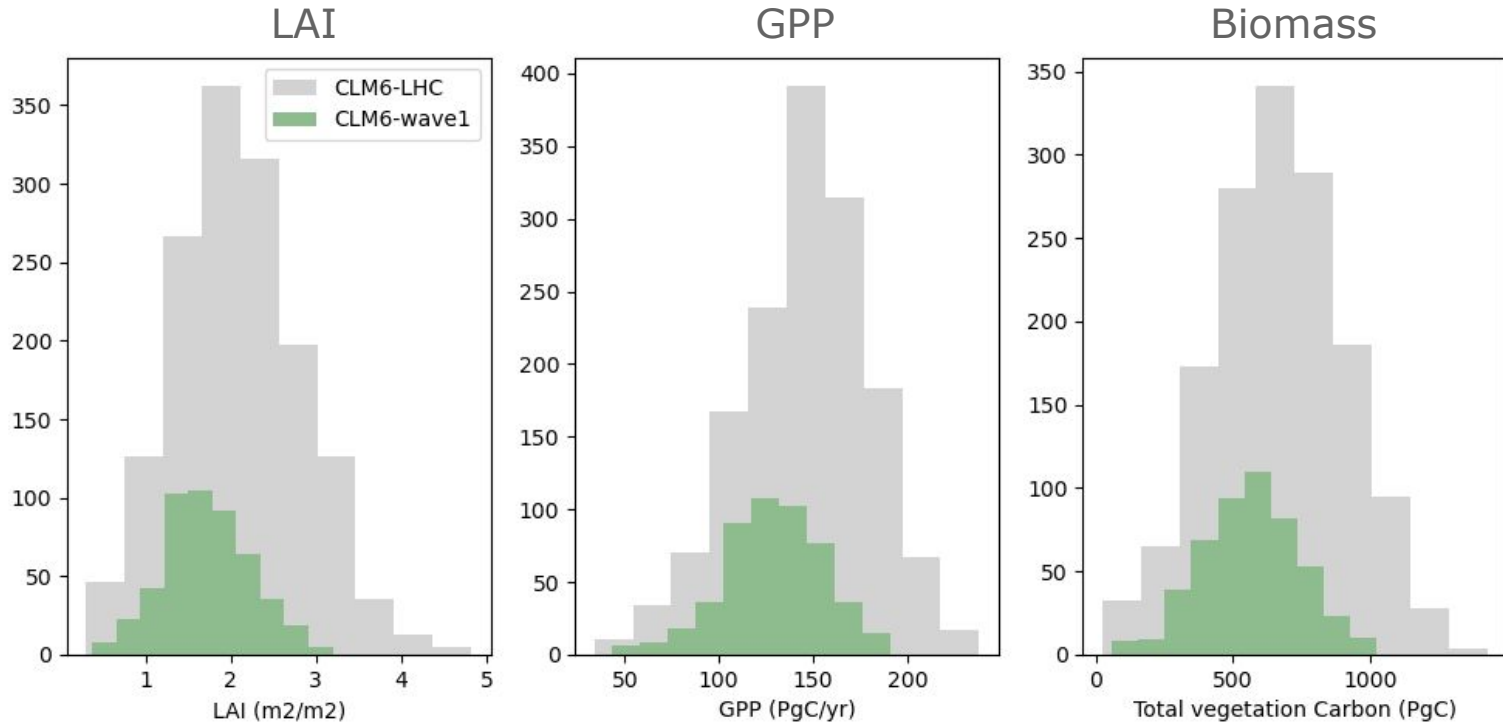
- Sample
- Emulate
- Score (cost function)
- Select best 500 parameter sets



Results (global mean)

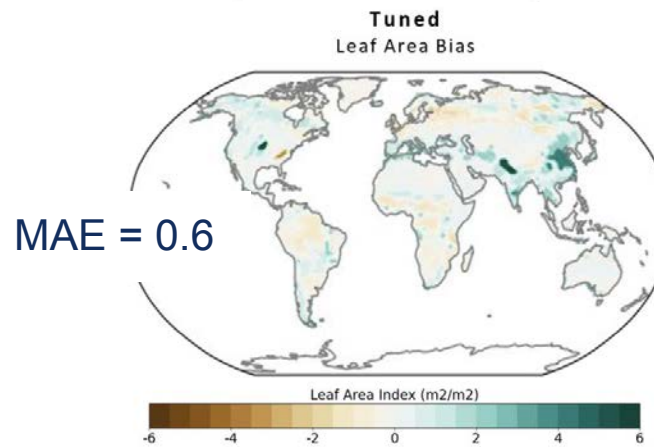
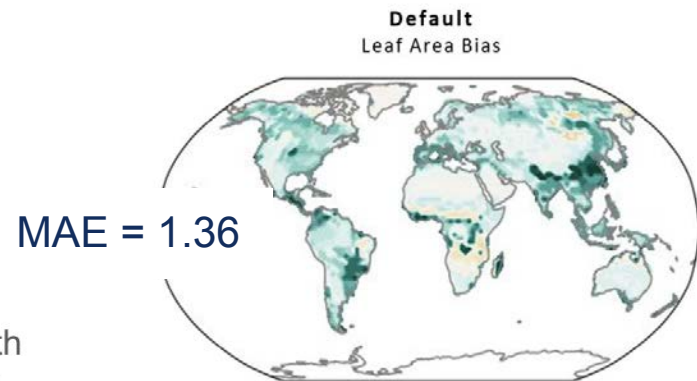
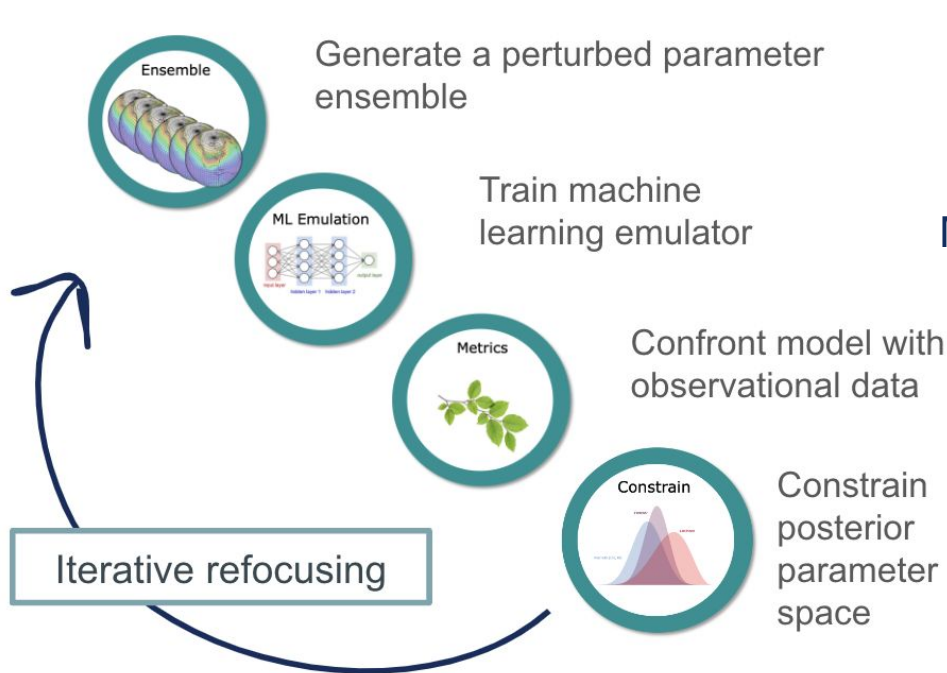


Results (global mean)



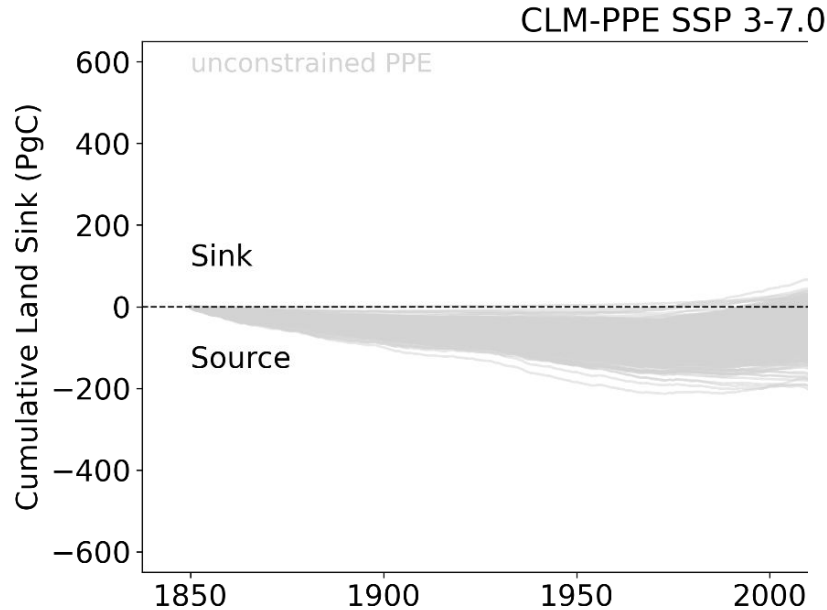
LEAP

Towards global parameter calibration (testing with LAI calibration)



Constraining land carbon cycle projections

500 land-only simulations
with Latin Hypercube generated
parameter sets (25 parameters)

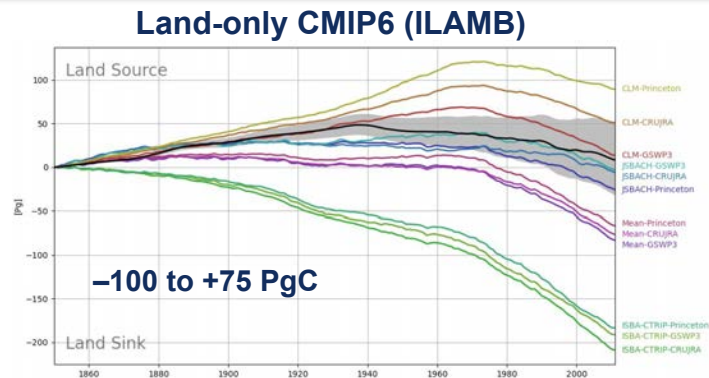
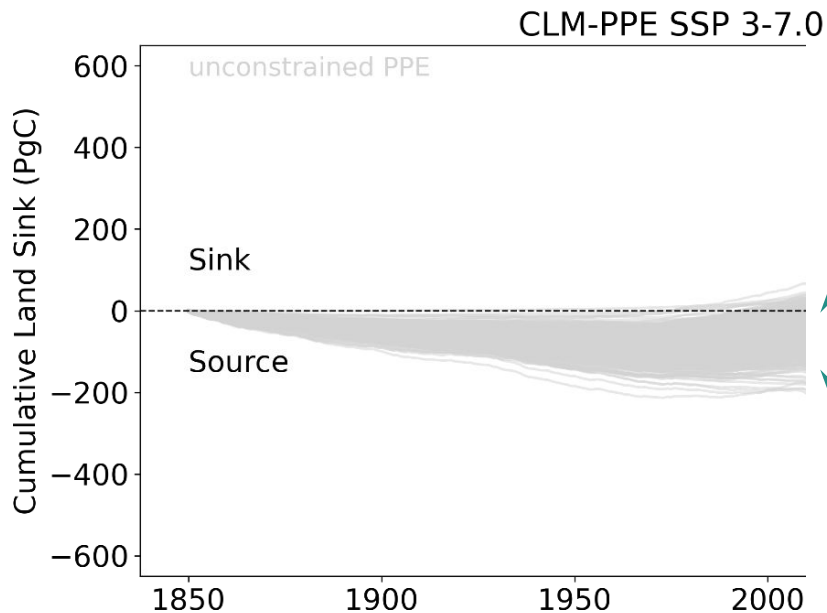


Important params for Leaf Area Index

Parameter	Param type
jmaxb0	Photosynthesis
jmaxbl	
wc2wjb0	
theta_cj	
leafcn (PFT)	
jmaxha	
tpu25ratio	Soil hydrology
hksat_sf	
fff	
sucsat_sf	Plant water use
d_max	
kmax (PFT)	
medlynslope (PFT)	
medlynintercept (PFT)	
crit_dayl	Phenology
soilpsi_off	Leaf physiology
leaf_long (PFT)	
slatop (PFT)	
lmr_intercept_atkin	Respiration
lmrha	Allocation
froot_leaf (PFT)	
FUN_fracfixers (PFT)	Nitrogen uptake
pc	Snow

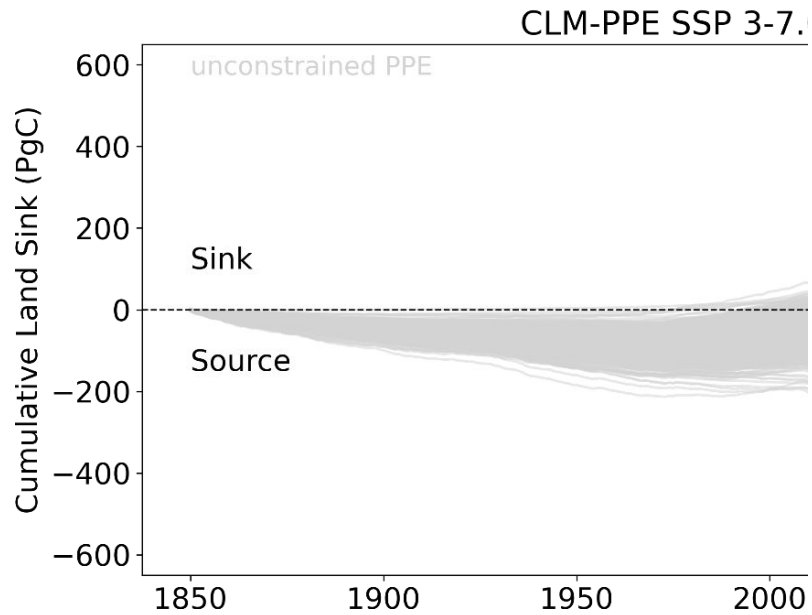
Constraining land carbon cycle projections

500 land-only simulations with Latin Hypercube generated parameter sets (25 parameters)



Constraining land carbon cycle projections

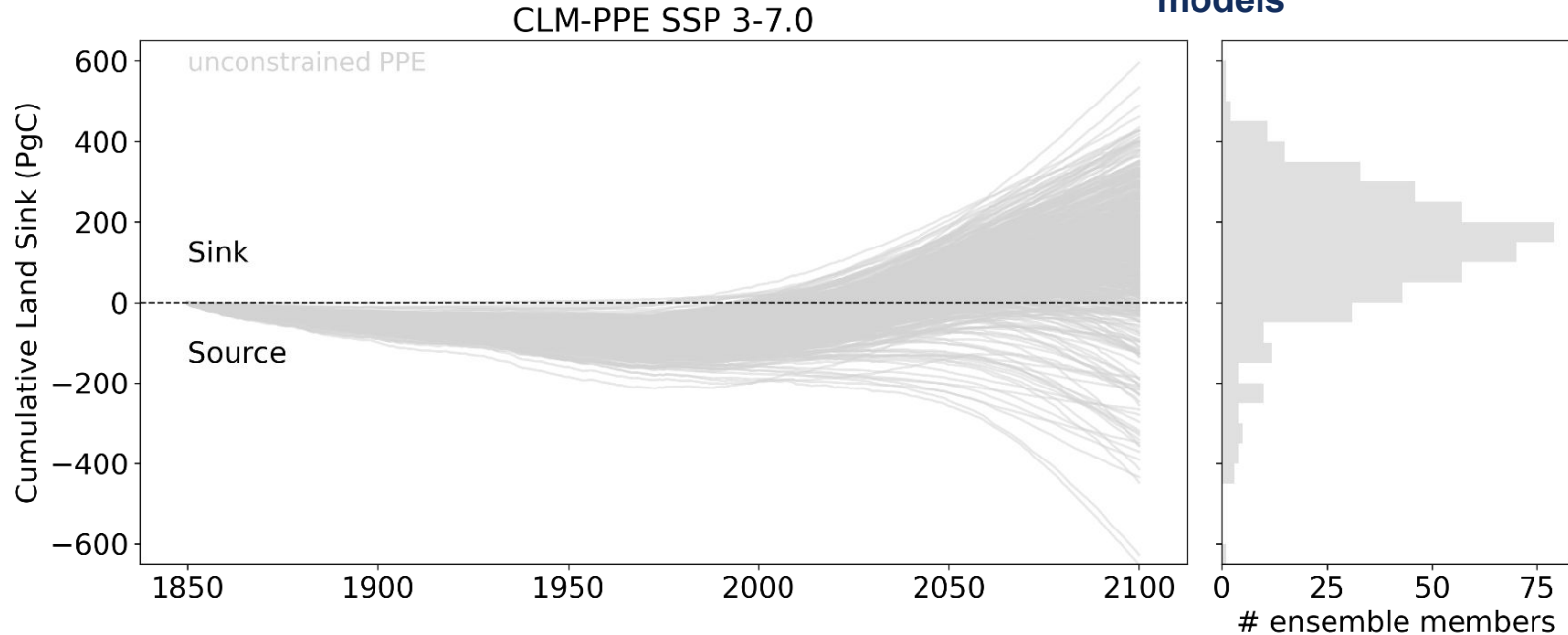
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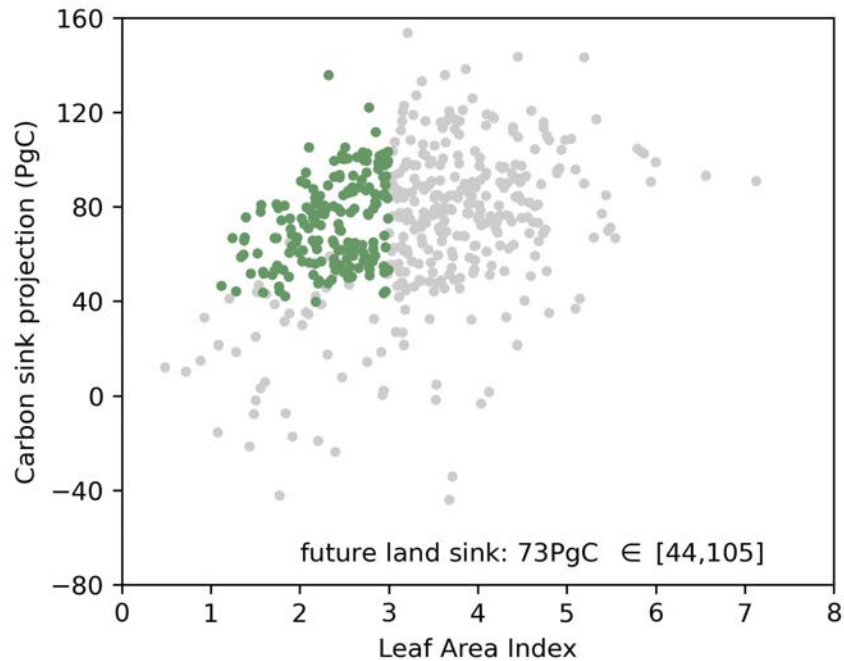
Constraining land carbon cycle projections

500 land-only simulations
with latin hypercube generated
parameter sets (25 parameters)

**Range $\pm 600\text{PgC}$ is as
large as across CMIP6
models**



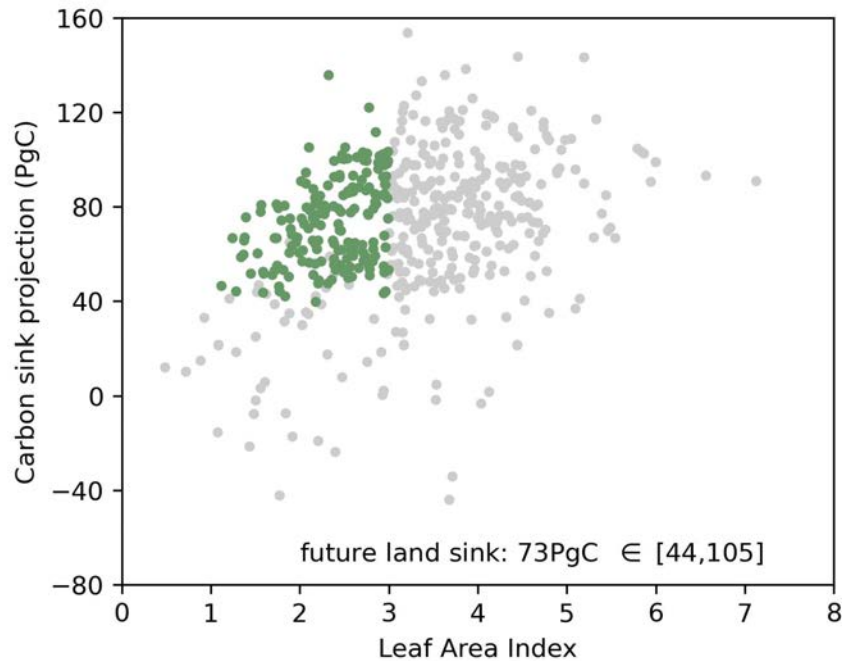
Constraining land carbon cycle projections (history matching)



Can we constrain by retaining only parameter sets with reasonable values for 'observed' quantities?

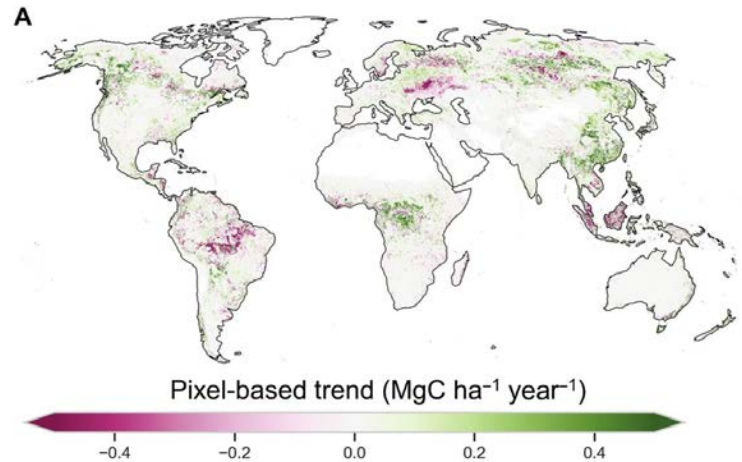
- leaf area index mean / trend

Constraining land carbon cycle projections (history matching)



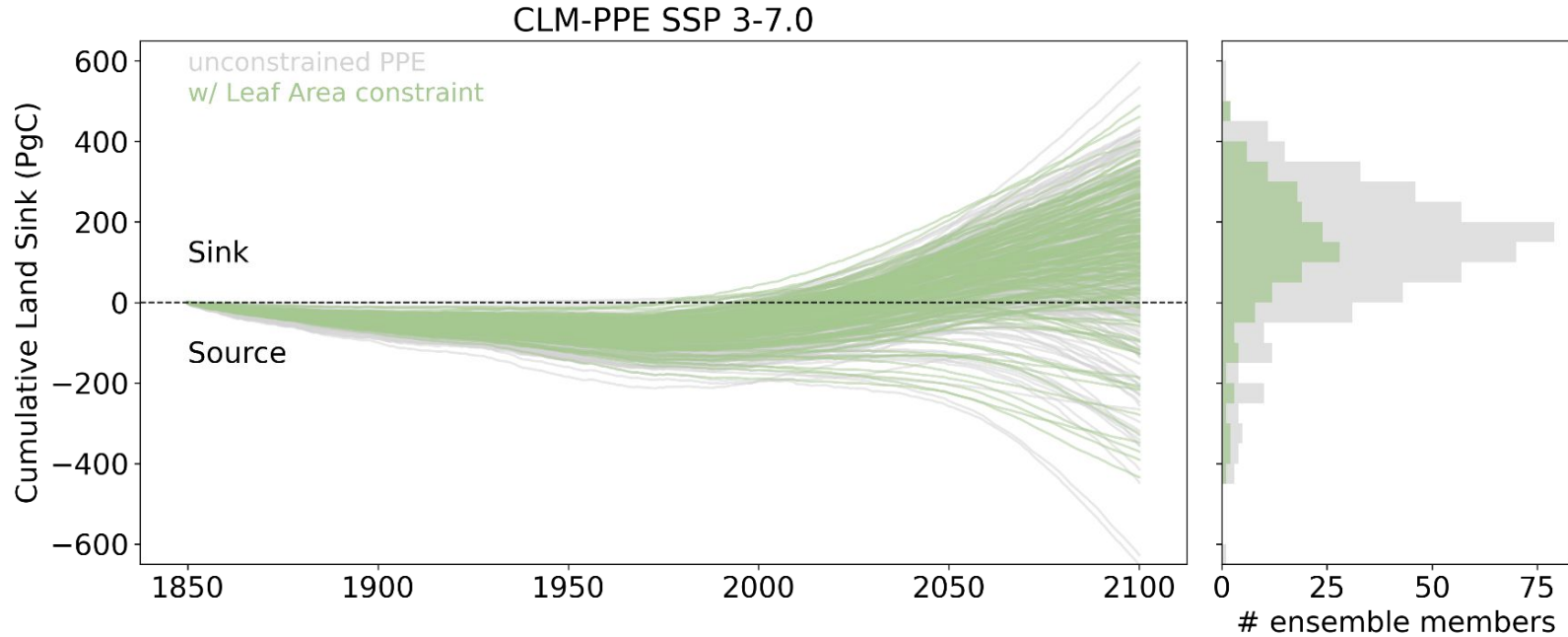
Can we constrain by retaining only parameter sets with reasonable values for ‘observed’ quantities?

- leaf area index mean / trend
- total land use flux (e.g., from bookkeeping models)
- recent changes in live woody biomass from inventories/satellite (Xu et al, 2021)



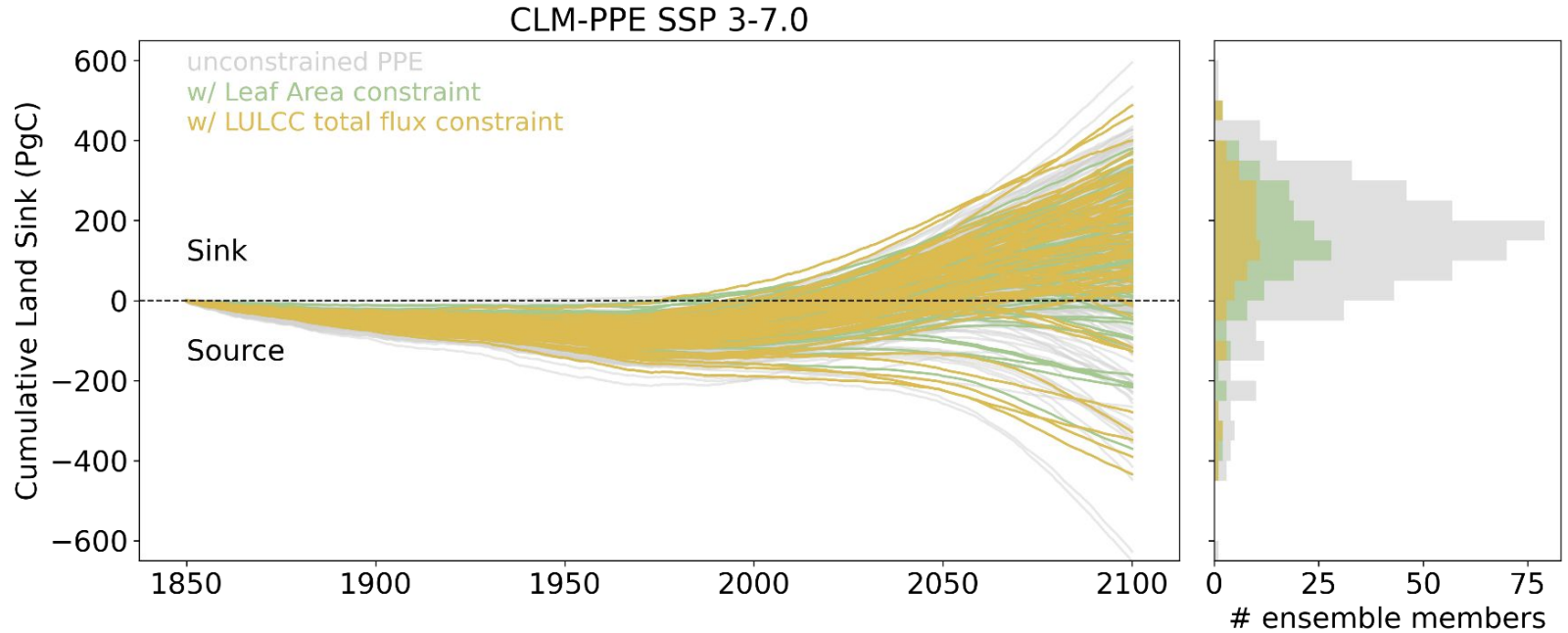
Constraining land carbon cycle projections

500 land-only simulations
with Latin Hypercube generated
parameter sets (25 parameters)



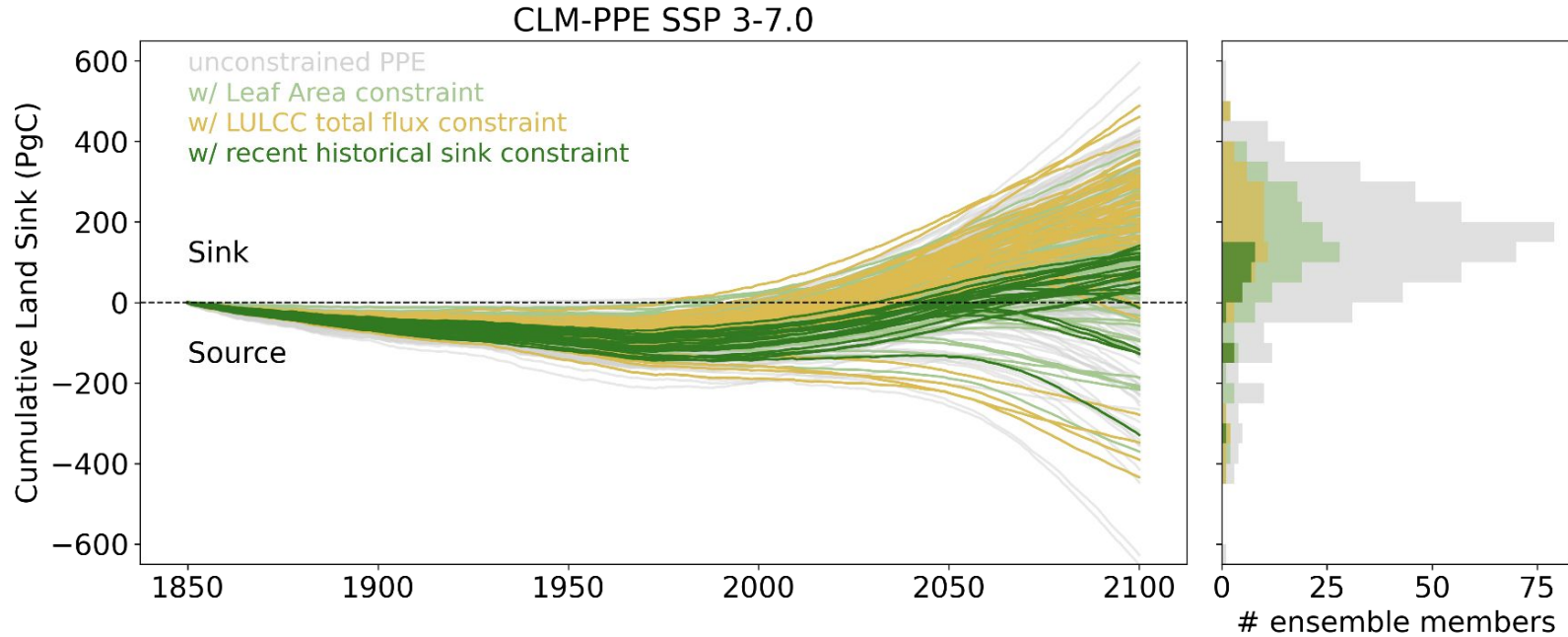
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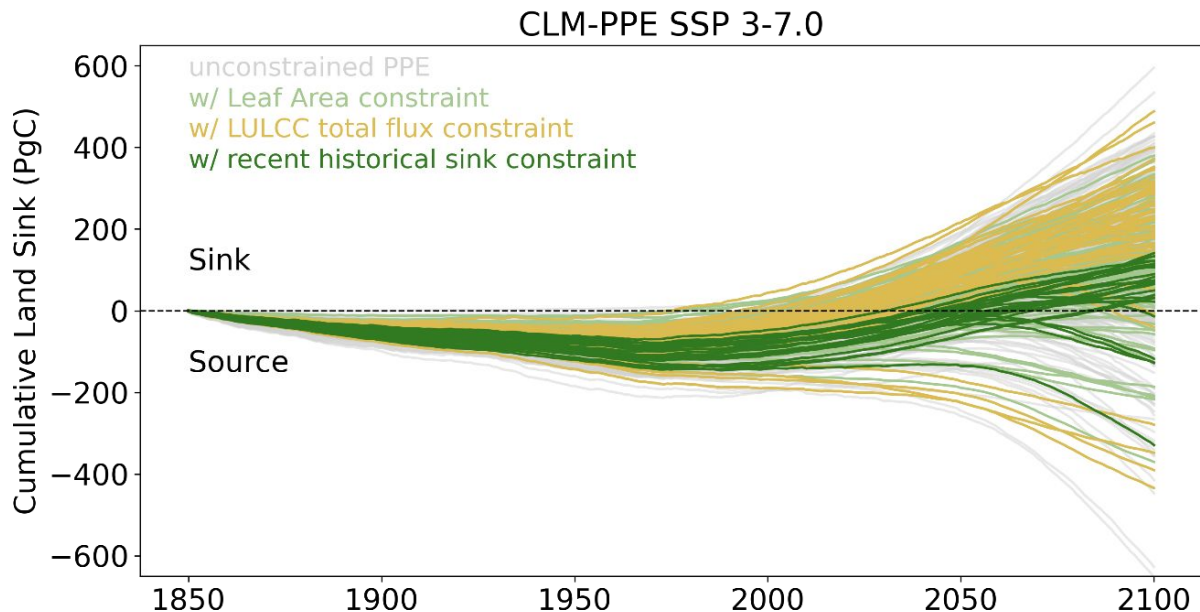
Constraining land carbon cycle projections

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Constraining land carbon cycle projections

500 land-only simulations
with Latin Hypercube generated
parameter sets (25 parameters)



Still a diversity of carbon trend responses, even in constrained sets, but range is much smaller

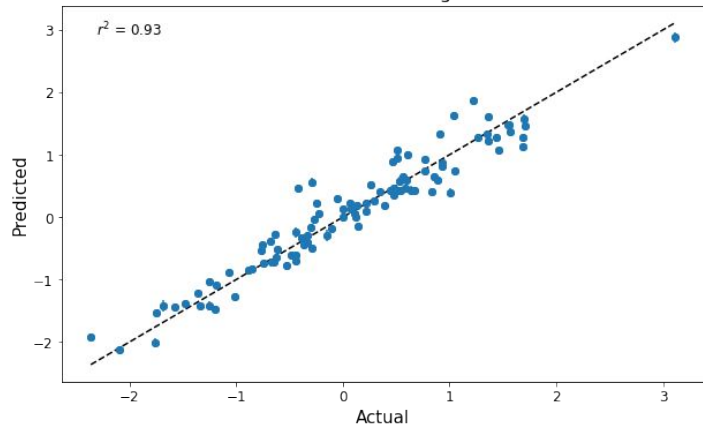
Can we build a future emissions-driven Large Ensemble by including multiple land carbon parameter sets to span this uncertainty as another ensemble dimension (in addition to Initial conditions)?

Parameter Estimation challenges (incomplete list)

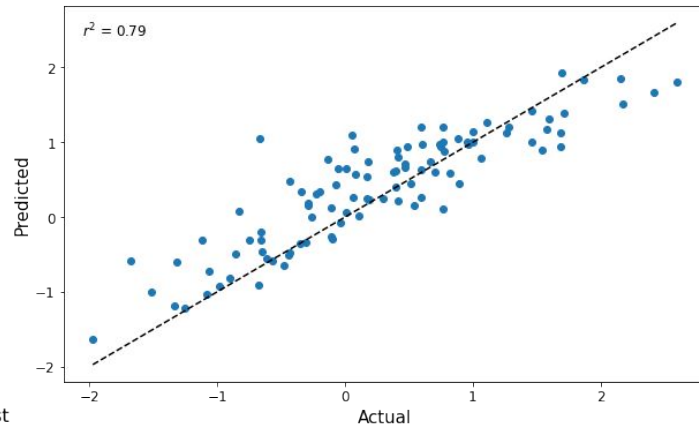


Many emulation algorithms with differing performance

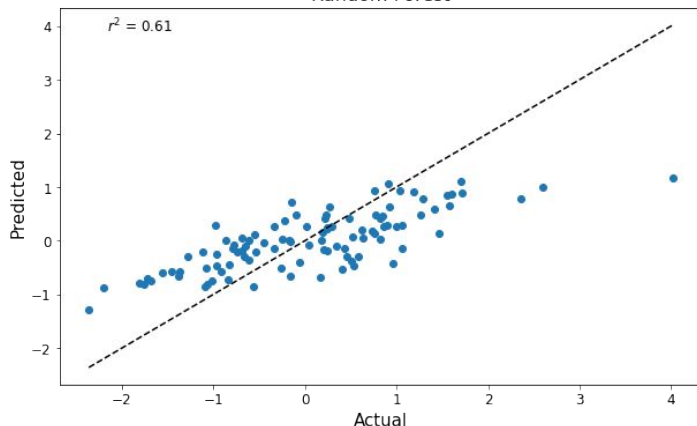
Gaussian Process Regression



Artificial Neural Network



Random Forest



Emulating global annual mean leaf area index

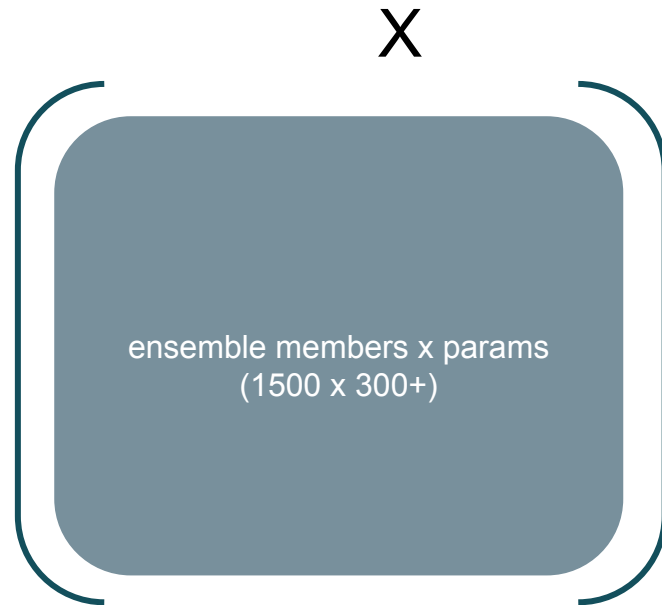
****Preliminary****
hyperparameter tuning in progress!

Thanks to the EEm Python package:
<https://github.com/duncanwp/EEm>
Watson-Parris et al. 2021

Challenges with PFT parameters

To reduce regional biases, need to be able to tune PFT parameters independently

- 1) Too many parameters (10-15 PFT parameters x 16 PFTs = 300+)

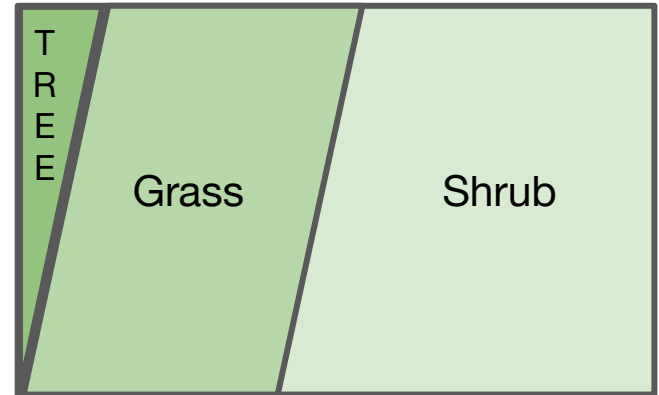


Challenges with PFT parameters

To reduce regional biases, need to be able to tune PFT parameters independently

- 1) Too many parameters (10-15 PFT parameters x 16 PFTs = 300+)
- 2) Most observational datasets are not disaggregated by PFT

Fractional PFT coverage in 1 gridcell



Challenge: Coupled vs Land-only parameter impacts

Impact of parameter perturbations can be different in Coupled vs Land-only (offline) simulations, even exhibiting a different sign of response

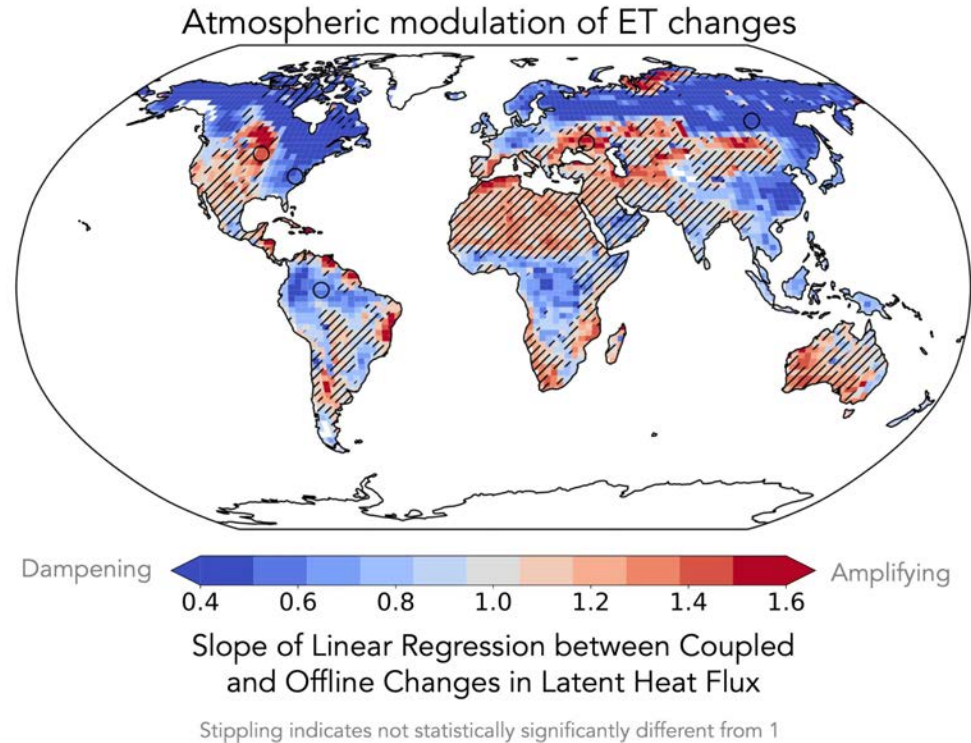


Figure from Zarakas et al., in review

Parameter Estimation challenges (incomplete list)

- As you add constraints (new obs variables and/or constraints beyond means like annual cycle amplitude, interannual variability, trends) → possible to likely that cannot find reasonable parameter sets that meet all constraints → structural errors
- Calibrating the whole model all at once is likely impractical as model complexity rises (e.g., FATES full competition mode)
 - Calibration cascade methodology likely needed

Calibrated Land Model Intercomparison Project (CaLMIP): Planning & Development Workshop

Virtual Workshop Dates

The workshop will consist of three sessions, each lasting 1.5 hours. To accommodate participants across different time zones, we are offering two time options per session: one for the eastern US/EU time zones and one for the Western US/Australia/Asia time zones.

- Session 1: Thursday, March 6 at 8:00-9:30 pm EST OR Friday, March 7 at 10:00-11:30 am EST ([time zone converter](#))
- Session 2: Wednesday, March 19 at 10:00-11:30 am EDT OR Wednesday, March 19 at 8:00-9:30 pm EDT ([time zone converter](#))
- Session 3: Tuesday, April 1st at 10:00-11:30 am EDT OR Tuesday, April 1st at 8:00-9:30 pm EDT ([time zone converter](#))

Workshop Organizers

Natasha MacBean, Nina Raoult, Natalie Douglas, Jana Kolassa, Tristan Quaife, Istem Fer, Daniel Kennedy, Linnia Hawkins, Katie Dagon, Hannah Liddy

Next-generation Earth System modeling to address urgent mitigation and adaptation needs

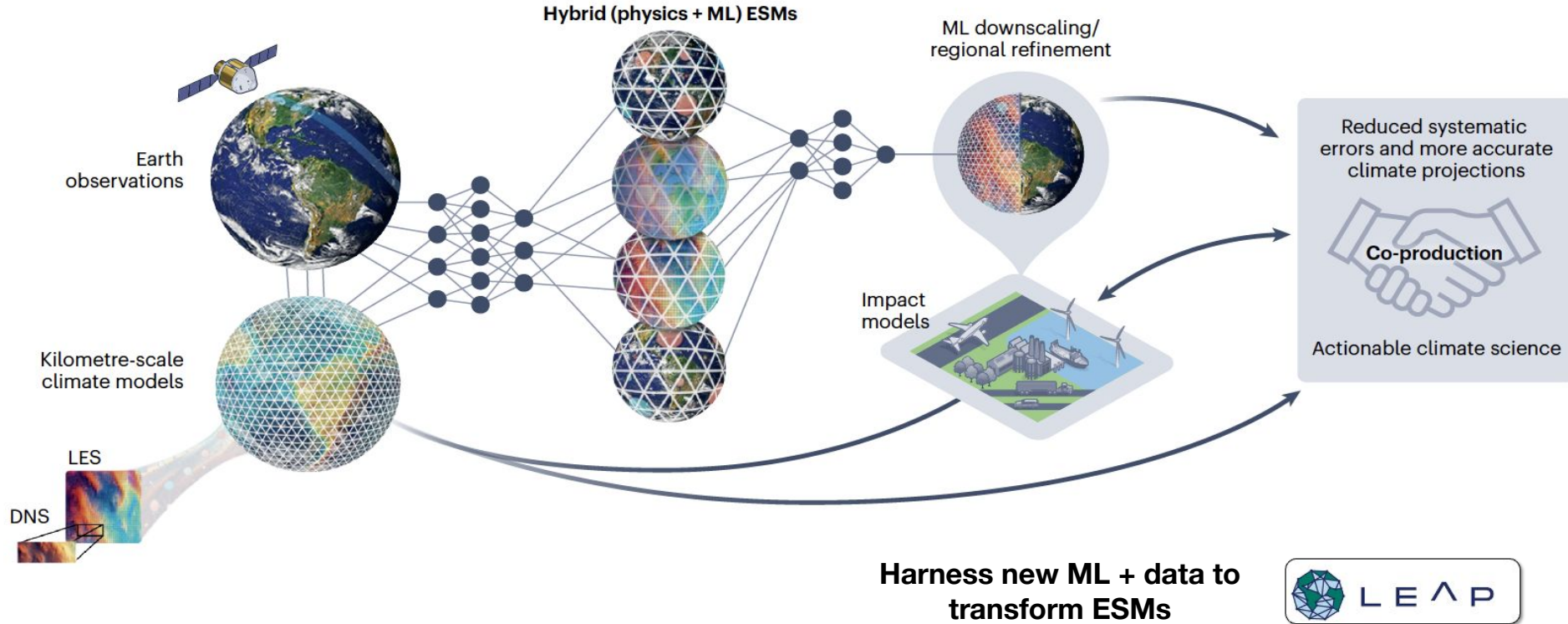


Figure from Eyring, Gentine, Camps-Valls, Lawrence, Reichstein (Nature Climate Change, 2024)

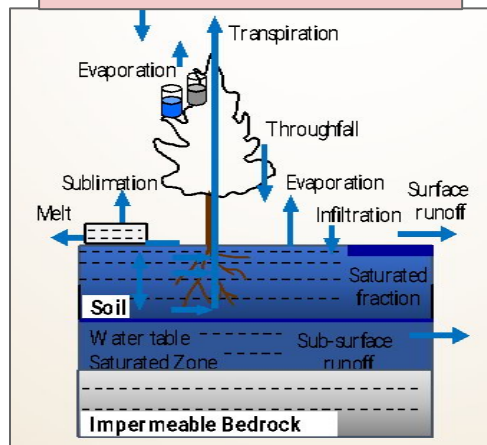
*LEAP forward in the **reliability**, **utility**, and **reach** of climate projections through synergistic innovations in data science and climate science*

Thank you!

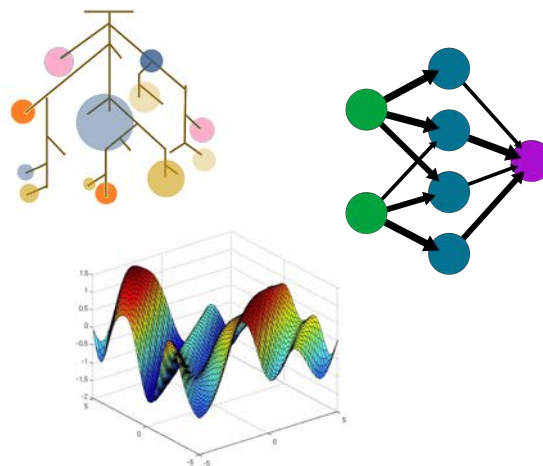


Machine Learning for Land Model Emulation

Input: **x number** of land model parameter values



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



Output: land **variable/metric** of interest

