Machine Learning for Land Modeling

Linnia Hawkins & Katie Dagon

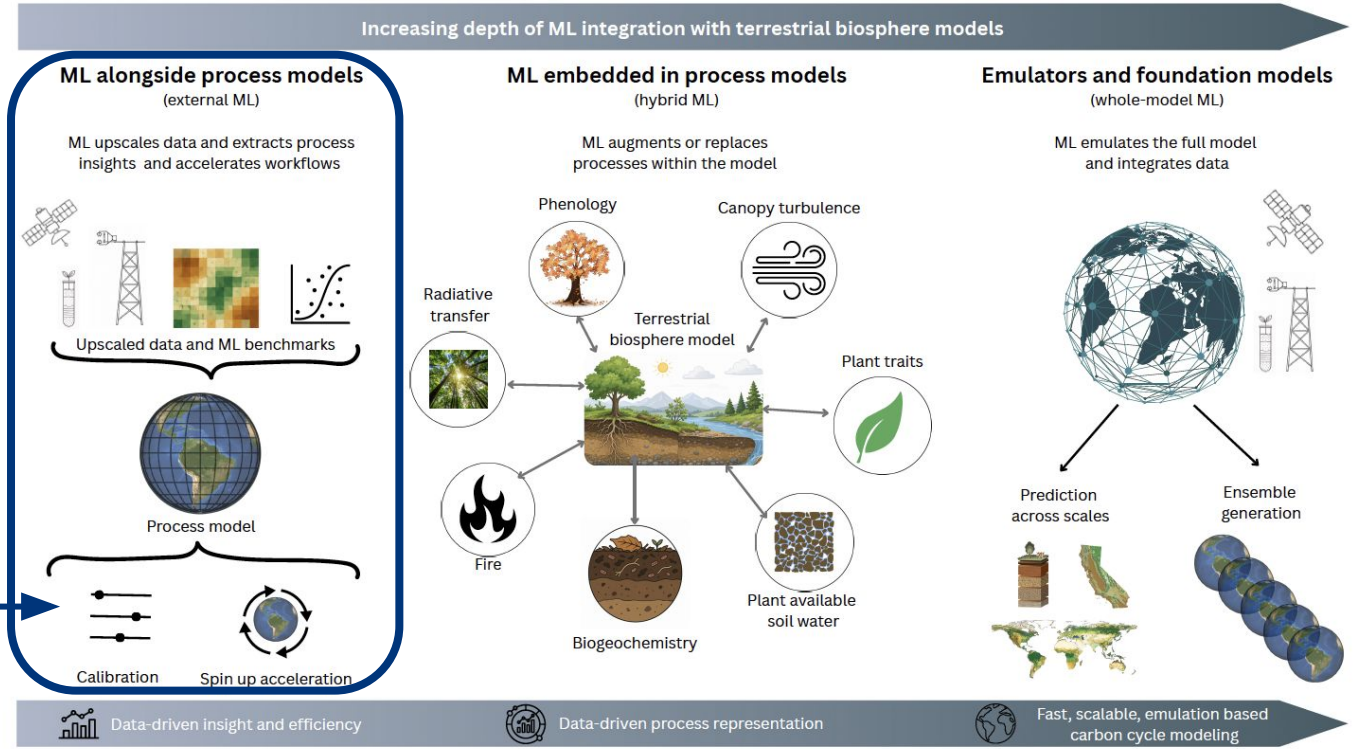
With contributions from: Maoya Bassiouni, Jianing Fang, Adrianna Foster, Pierre Gentine, Yanghui Kang, Daniel Kennedy, Dave Lawrence, Aya Lahlou, Kirsten Mayer, Nina Raoult, Addisu Semie, Guoqiang Tang, Andy Wood, Weiwei Zhan

CLM Tutorial 2026
November 18, 2026



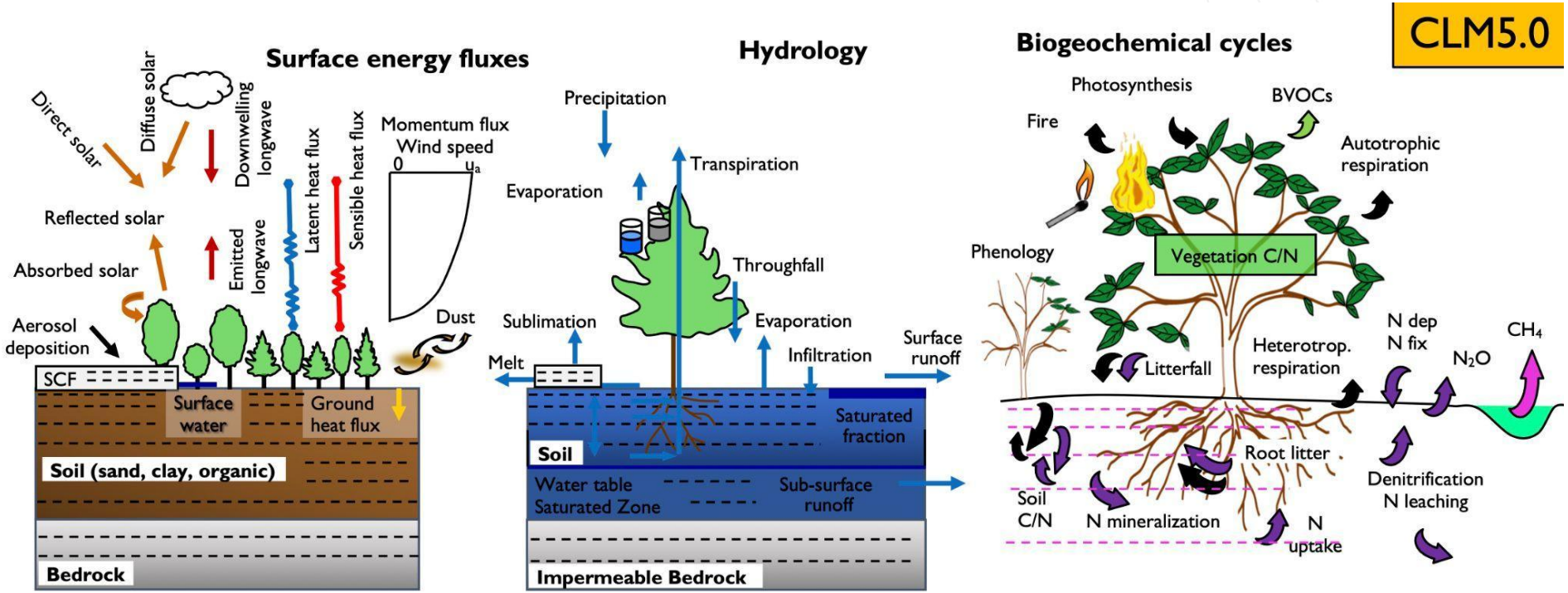
Machine Learning for Land Modeling

We'll focus on how ML is used for **parameter estimation**



Hawkins et al., *accepted*

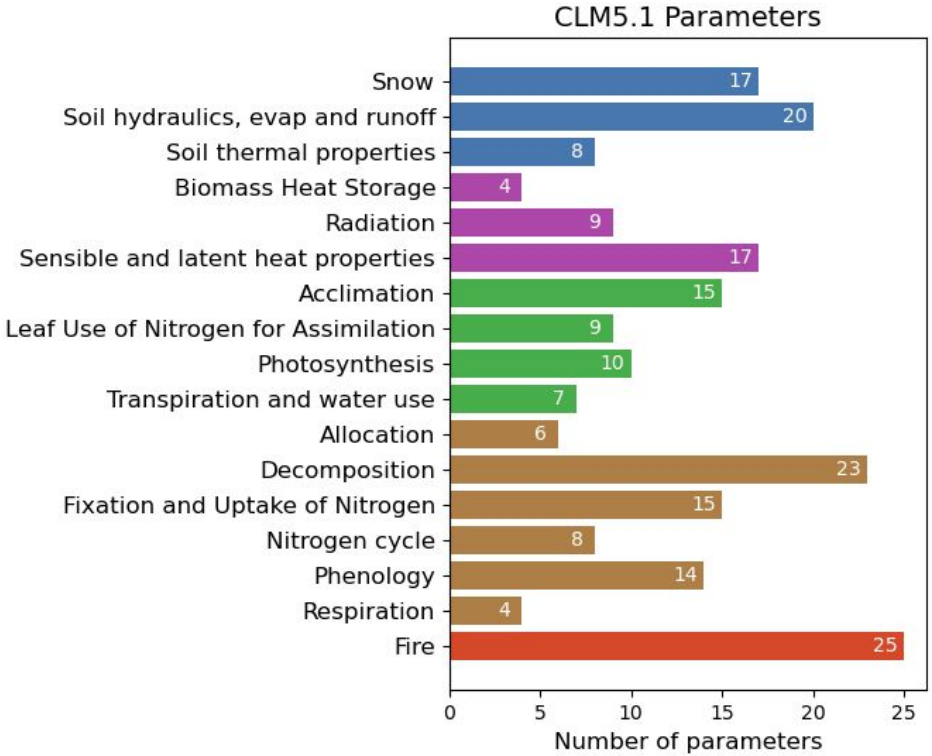
What is a parameter?

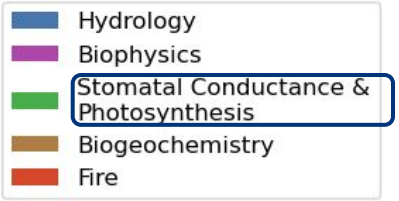


Schematic of the Community Land Model (CLM), version 5

Lawrence et al. (2019)

What is a parameter?





Let's look at an example parameter for **stomatal conductance**

Kennedy et al. (2025)

Where do parameter values come from?

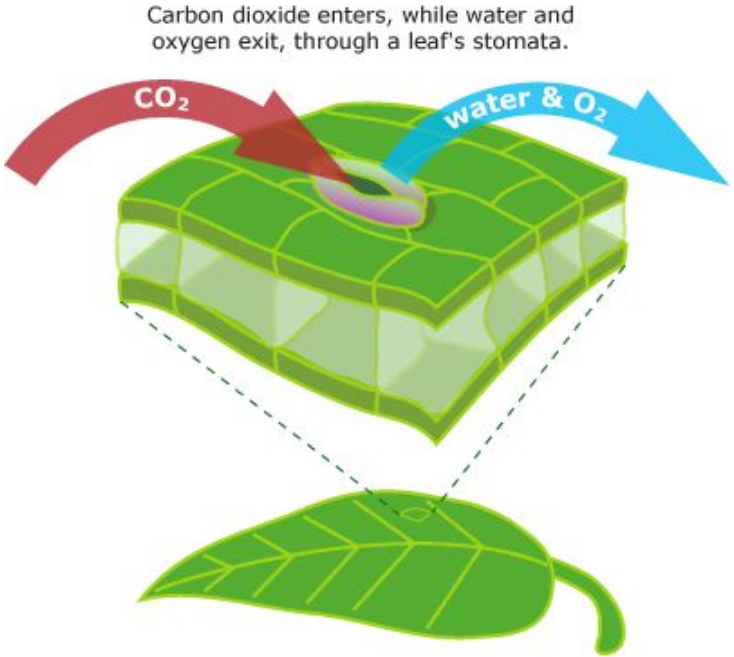
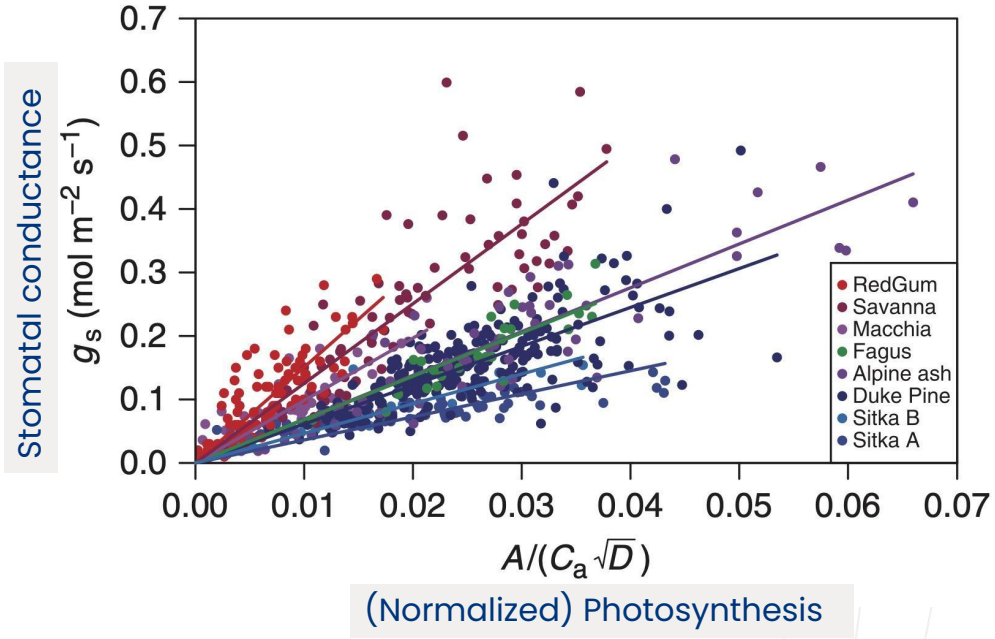


Image: evolution.berkeley.edu



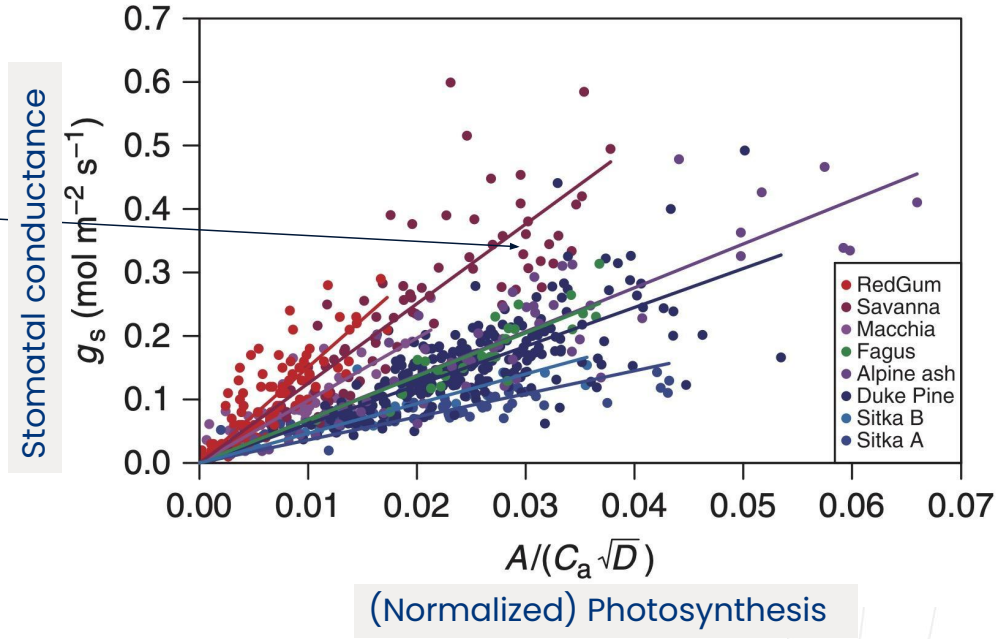
Medlyn et al. (2011)

Where do parameter values come from?

Slope parameter represents **marginal water cost of carbon gain** and is an important model parameter.

$$g_s = g_o + 1.6\left(1 + \frac{g_1}{\sqrt{D}}\right)\frac{A_n}{c_s/P_{atm}}$$

g_1 = slope parameter (mol H_2O/mol CO_2)



Medlyn et al. (2011)

Why is parameter estimation hard?

- **Large:** number of parameters
- **Slow:** change parameter, run model, analyze results, update parameter value(s), repeat
- **Complex:** difficult to predict/understand/identify parameter interactions
- **Ambiguous:** difficult to define objective "tuning targets" and quantify trade-offs between them

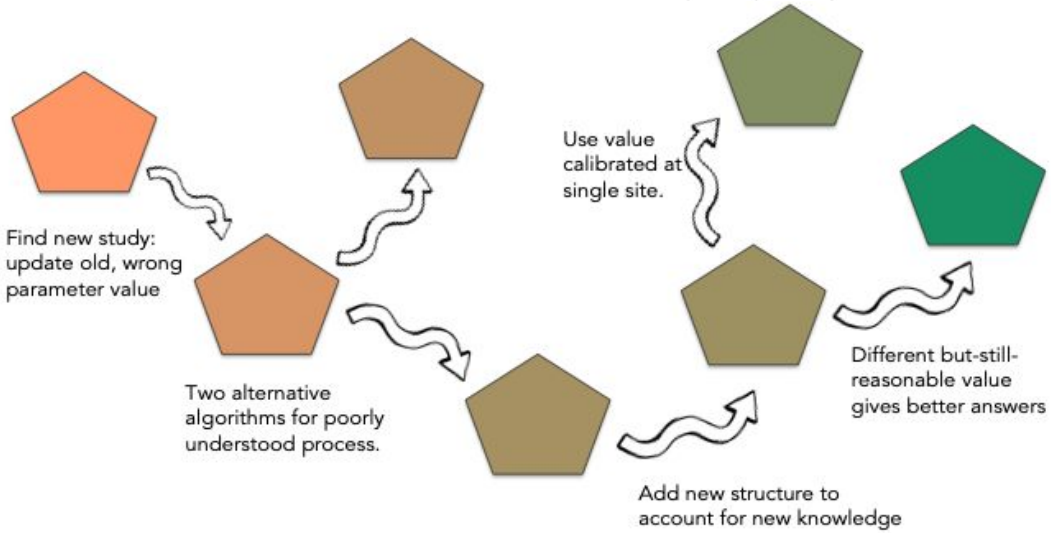
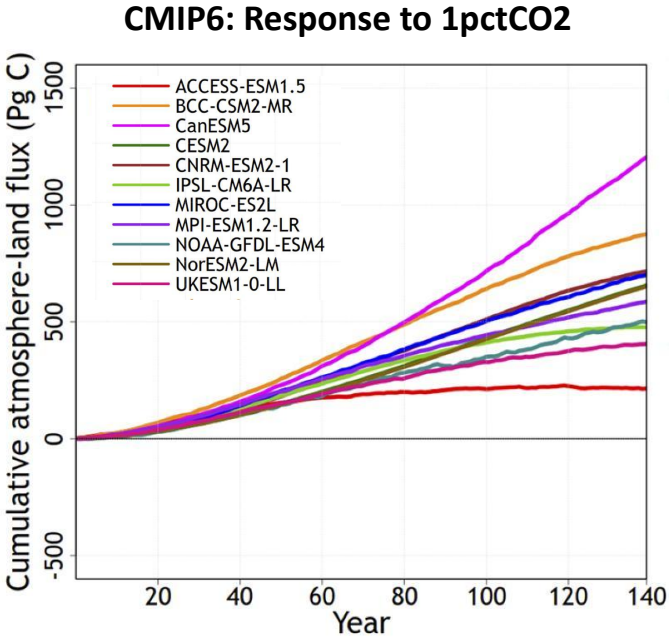


Figure from Rosie Fisher

What do we get out of parameter estimation?

- **Improved model realism:** keep pace with process representation as model complexity grows
- **Uncertainty quantification:** guide model development and constrain projections
- **Enhanced prediction skill:** accurate land states increase predictability
- **Actionable science:** provide an easily deployable tool for different study domains

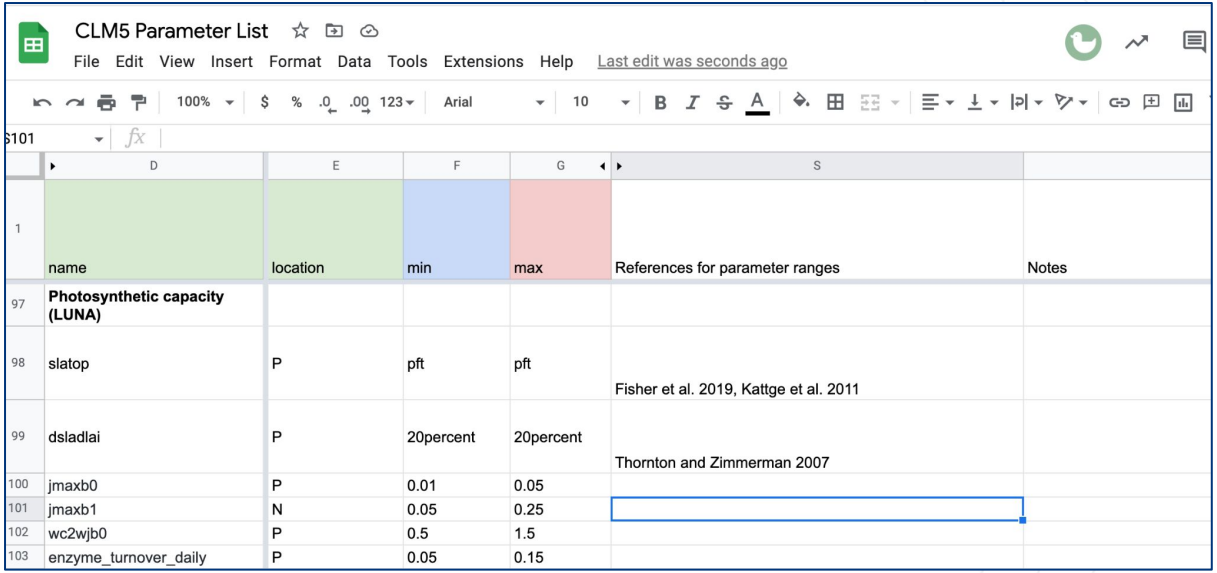


Arora et al. (2020)

Parameter sensitivity

How does changing a parameter setting effect model output?

- Change the setting of one parameter at a time.
- What are plausible values?
  - Table of CLM ranges



CLM5 Parameter List

File Edit View Insert Format Data Tools Extensions Help Last edit was seconds ago

	D	E	F	G	S	
1	name	location	min	max	References for parameter ranges	Notes
97	**Photosynthetic capacity (LUNA)**					
98	slatop	P	pft	pft	Fisher et al. 2019, Kattge et al. 2011	
99	dsladlai	P	20percent	20percent	Thornton and Zimmerman 2007	
100	jmaxb0	P	0.01	0.05		
101	jmaxb1	N	0.05	0.25		
102	wc2wjb0	P	0.5	1.5		
103	enzyme_turnover_daily	P	0.05	0.15		

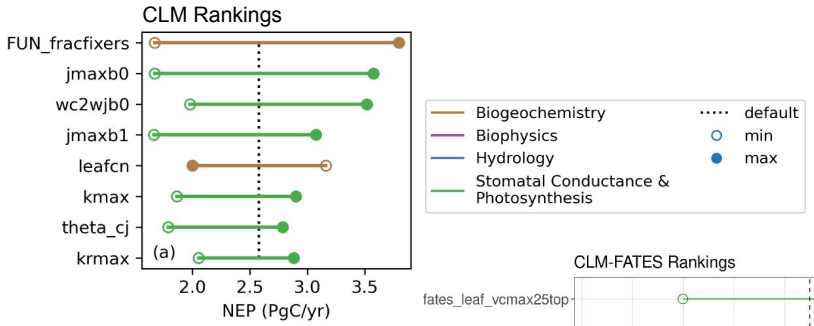
Parameter sensitivity

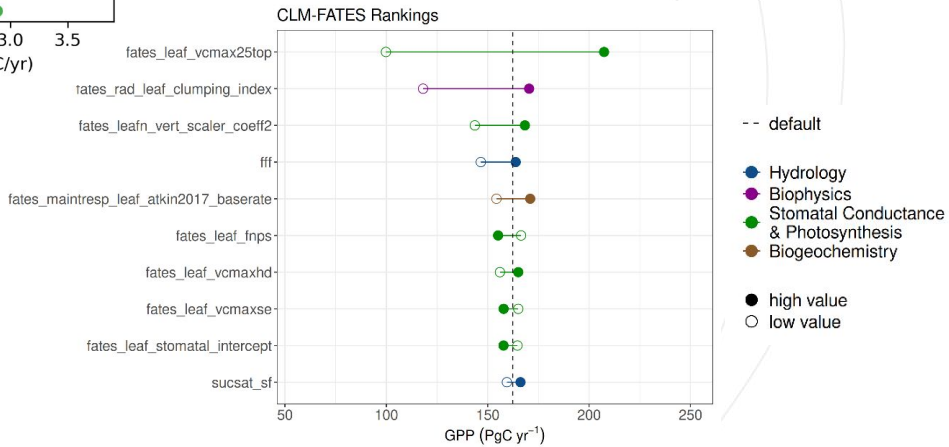
How does changing a parameter setting effect model output?





- Change the setting of one parameter at a time.
- What are plausible values?
  - Table of CLM ranges
- CLM sensitivity
  - Kennedy et al. (2025)
  - CLM website
- CLM-FATES sensitivity
  - Foster et al. (2026)
  - FATES website





Parameter sensitivity



CLM-FATES and CLM PPE | About this Study | Parameter Explorer | Ensemble Variance | Top Parameters | Model Comparisons | Parameter Information | Download Data

Parameter Explorer

Select a parameter and output variable to see how it affects model results. Only parameters with non-zero effects are listed.

Parameter: d_max

Variable: latent heat

Parameter: d_max

CLM parameter

Dry surface layer (DSL) parameter

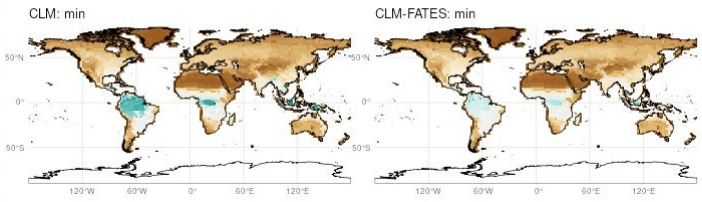
Summary Statistics

latent heat

Model	Default value ($W\,m^{-2}$)	Ensemble max value ($W\,m^{-2}$)	Ensemble min value ($W\,m^{-2}$)
CLM	42.470	40.409	43.167
CLM-FATES	40.180	37.960	40.944

Global Maps: annual means | Global maps: model differences | Climatology & Zonal Means

Annual means

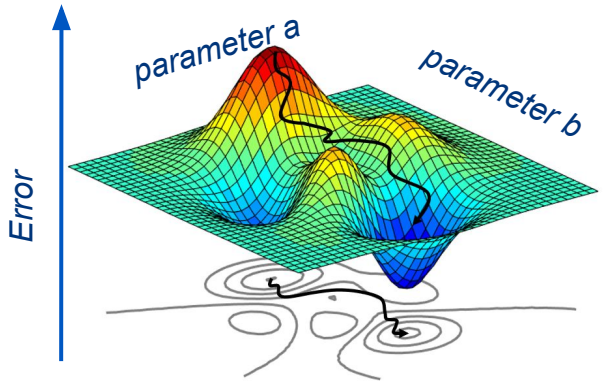


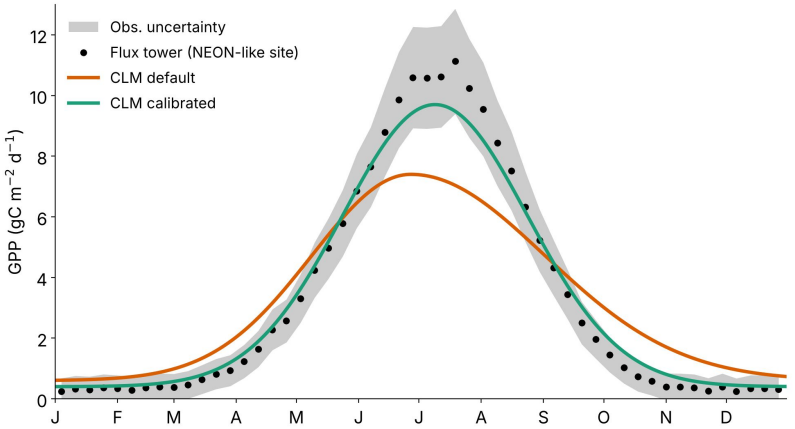
[FATES website]

Foster et al. [(2026)]

Parameter calibration

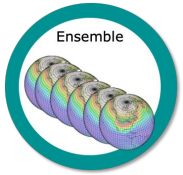
Finding parameter settings that improve agreement between model simulations and observations.





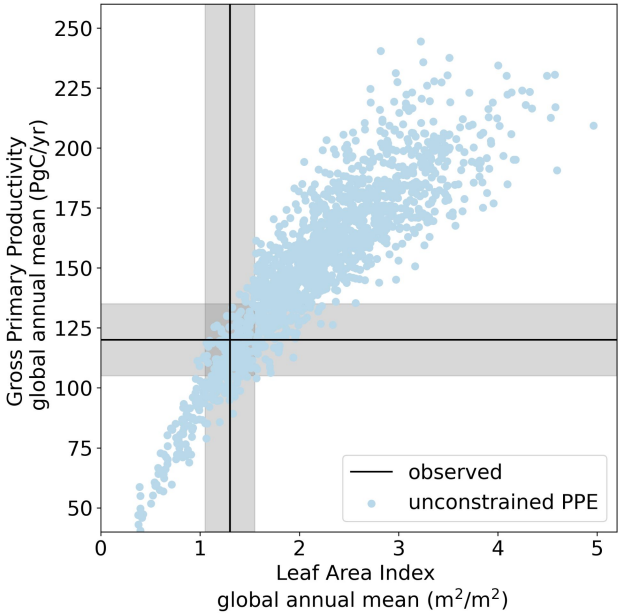
*Cartoon illustration *not real data*

Emulator-based parameter calibration

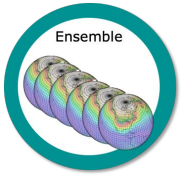


Generate multifactor PPE

- Latin hypercube sample

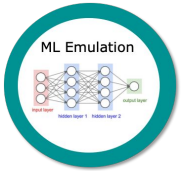


Emulator-based parameter calibration



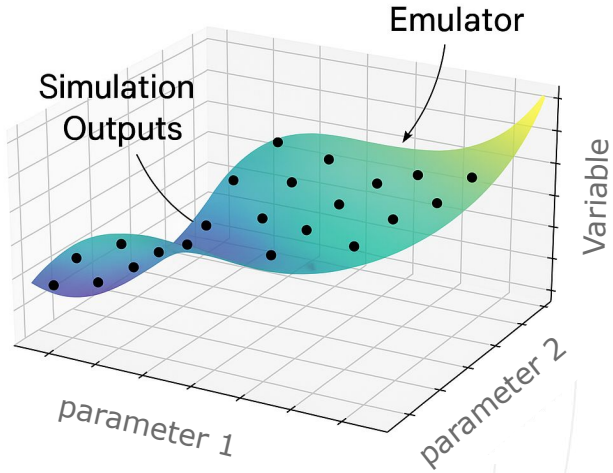
Generate multifactor PPE

- Latin hypercube sample

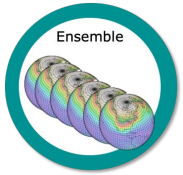


Train a ML emulator

- Fast surrogate for CLM
- Maps input parameters to CLM output metrics

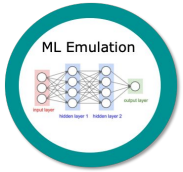


Emulator based parameter estimation



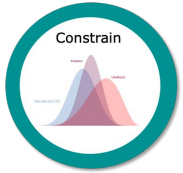
Generate multifactor PPE

- Latin hypercube sample



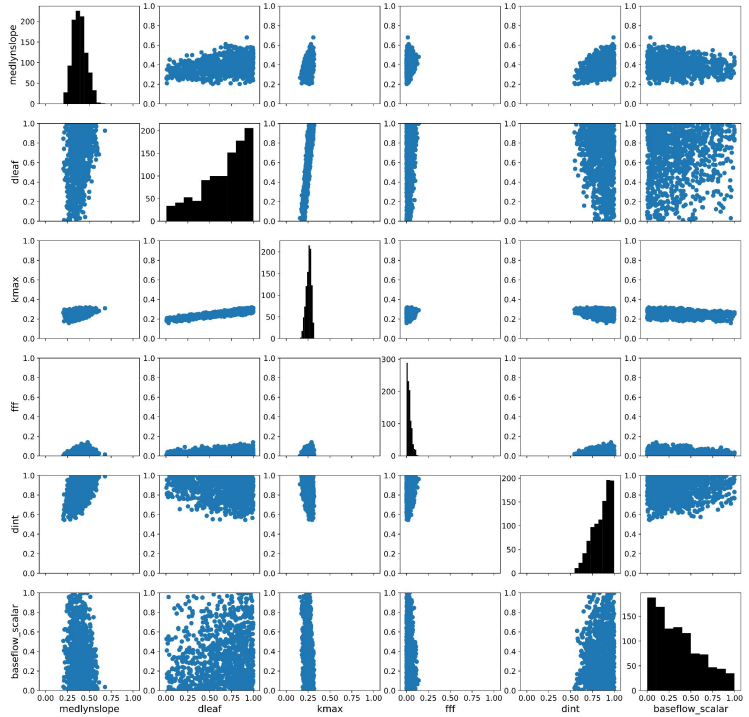
Train a ML emulator

- Fast surrogate for CLM
- Maps input parameters to CLM output metrics



Calibrate with emulator

- MCMC, gradient descent



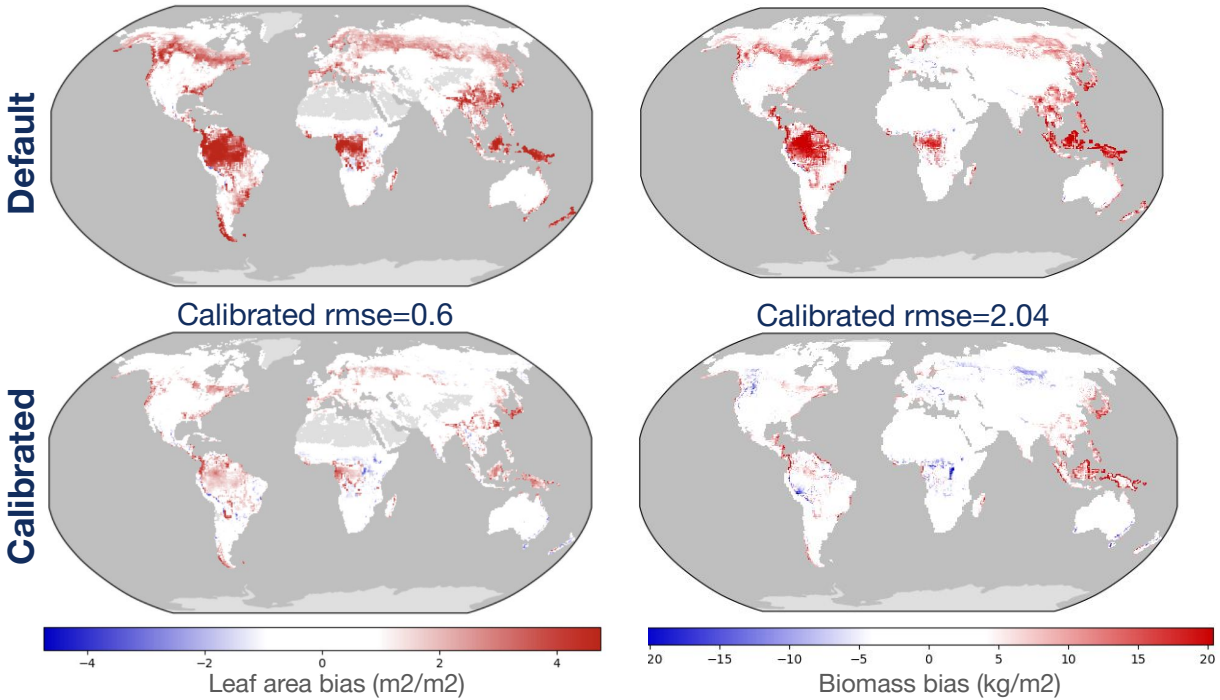
Dagon et al. (2020)

CLM6 calibration

Leaf Area Bias

Default rmse=1.36

Calibrated rmse=0.6

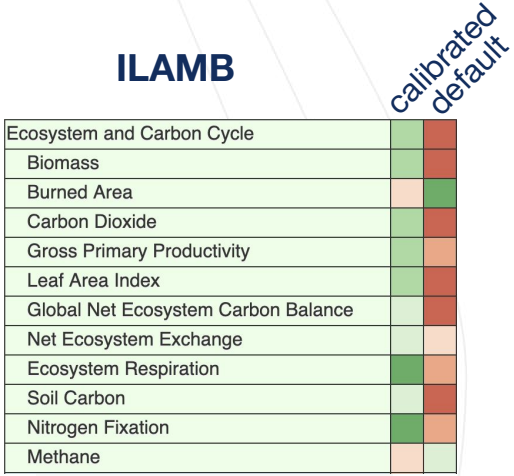


Biomass bias

Default rmse=4.09

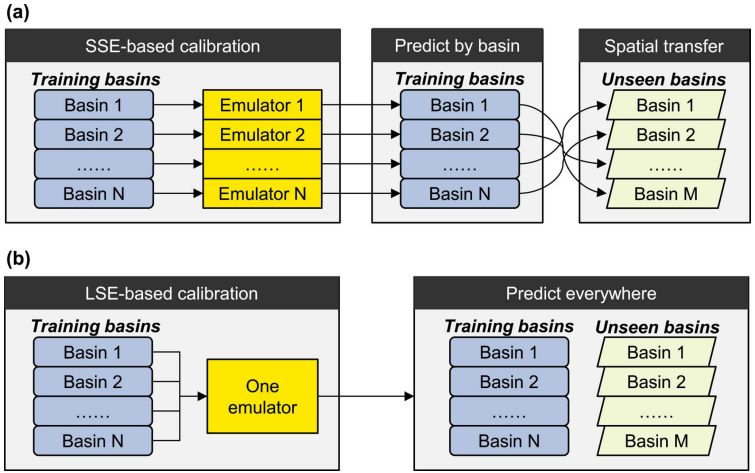
Calibrated rmse=2.04

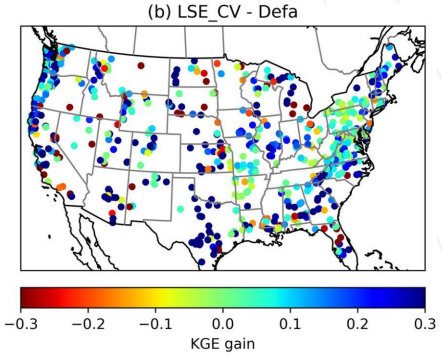
ILAMB



Calibrating CLM for hydrological applications

CAMELS basins in the CONUS
"A Large Sample Emulator approach consistently improves runoff predictions in all basins, outperforming the Single-Site Emulator in both single-objective and multi-objective calibration tasks."





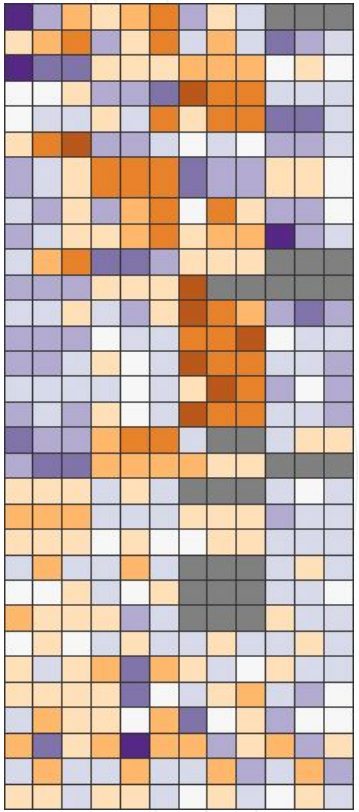




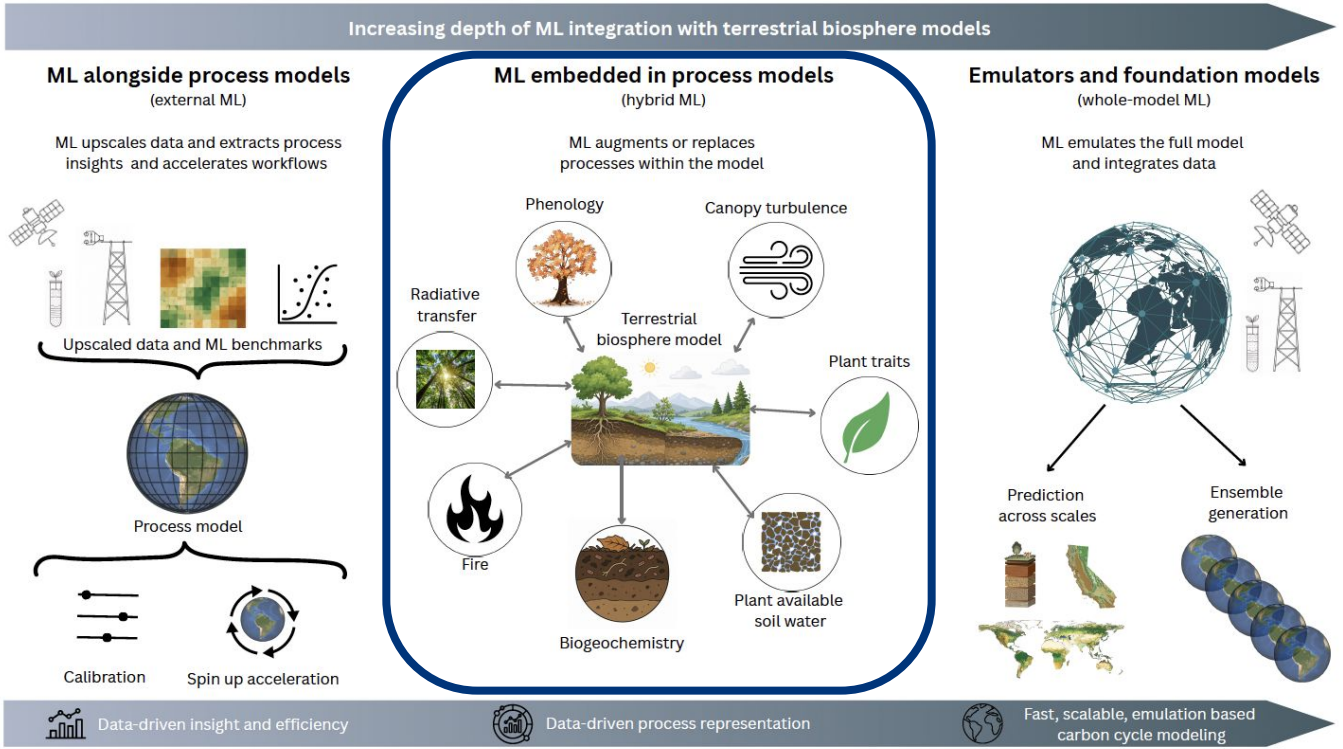
[Tang et al. (2025)]

Considerations for calibration

- Magnitude of uncertainty in observational data.
- Calibration methodology
  - *One optimal parameter set or an ensemble?*
  - *Computational expense*
  - *Spatial and temporal validation*
- Selecting parameters:
  - *CLM & FATES sensitivity experiments*
  - *Parameter ranges are subjective*
- Do I need to calibrate to address my research question?



Machine Learning for Land Modeling



Hawkins et al., accepted

Hybrid modeling

- Learn parameterizations from observational data
- Learn parameterizations from high resolution simulations
- Spatially distributed parameters
- Accelerate slow processes

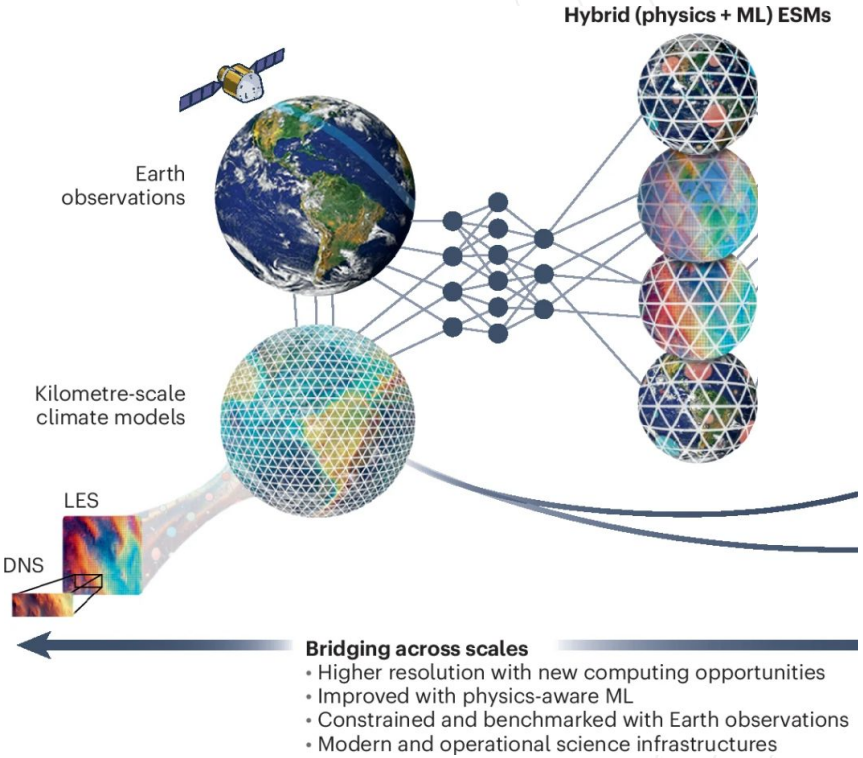


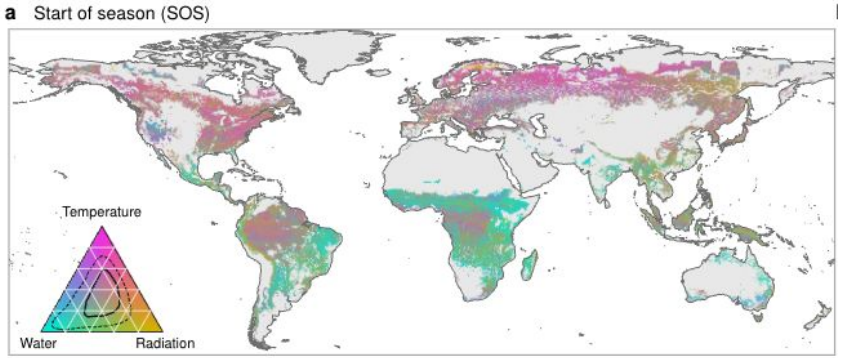
Figure modified from Eyring et al. 2024

Hybrid modeling example: Phenology

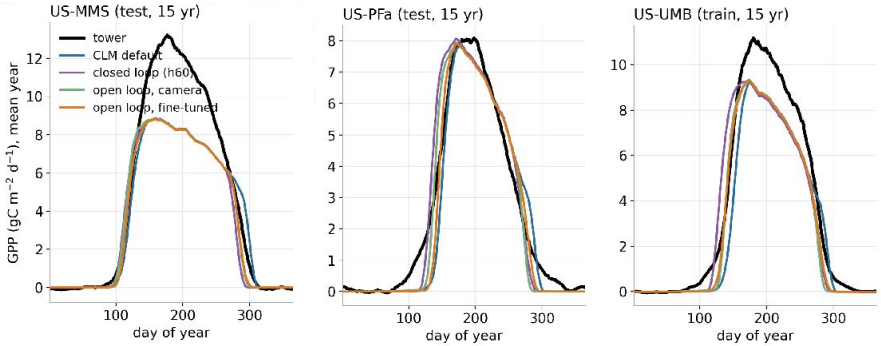
Aya Lahlou, Columbia University, LEAP



- Current CLM implementation is a function of growing degree days. Once threshold is reached leaf-out (senescence) is triggered.
- Trained ML parameterization on ERA and cSIF to improve prediction of phenological timing.



Meteorological controls on the timing of leaf-out (start of season).



Hybrid modeling in practice



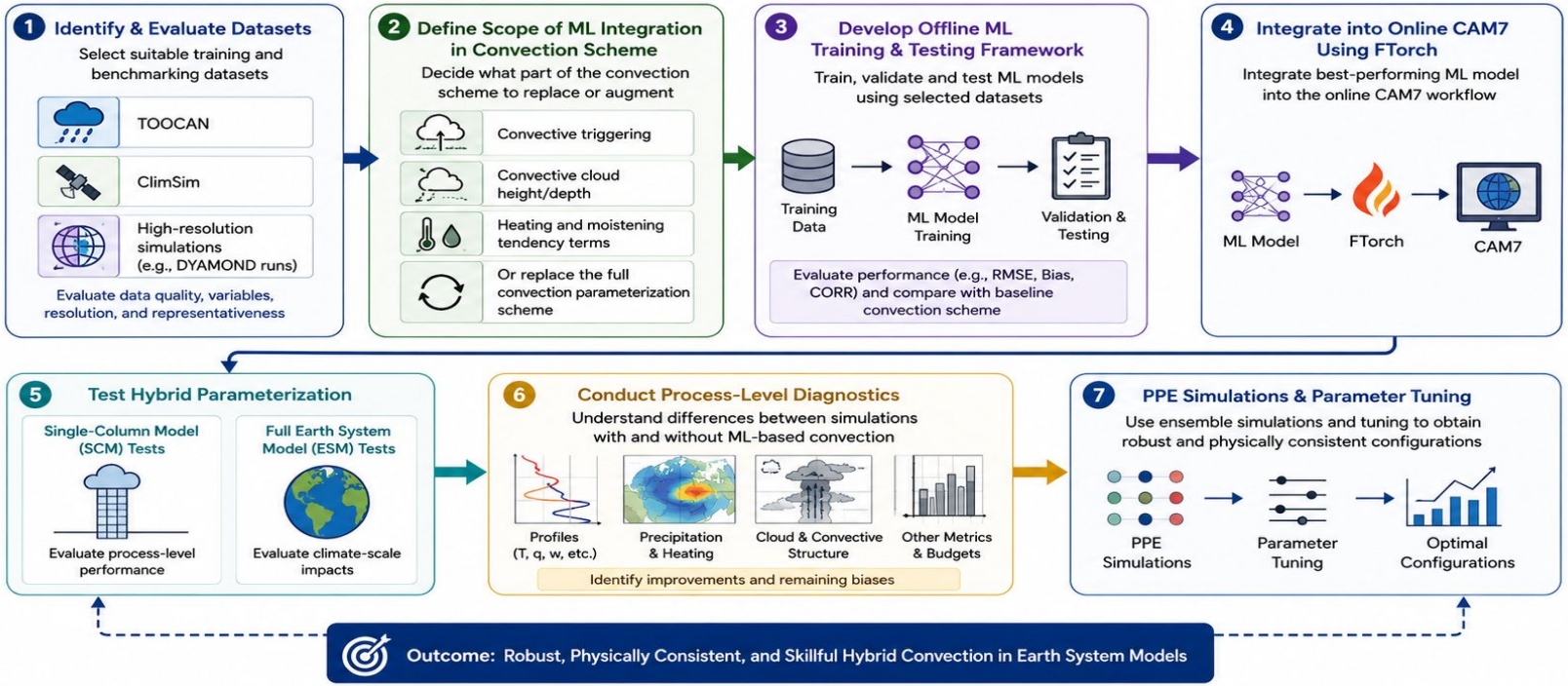
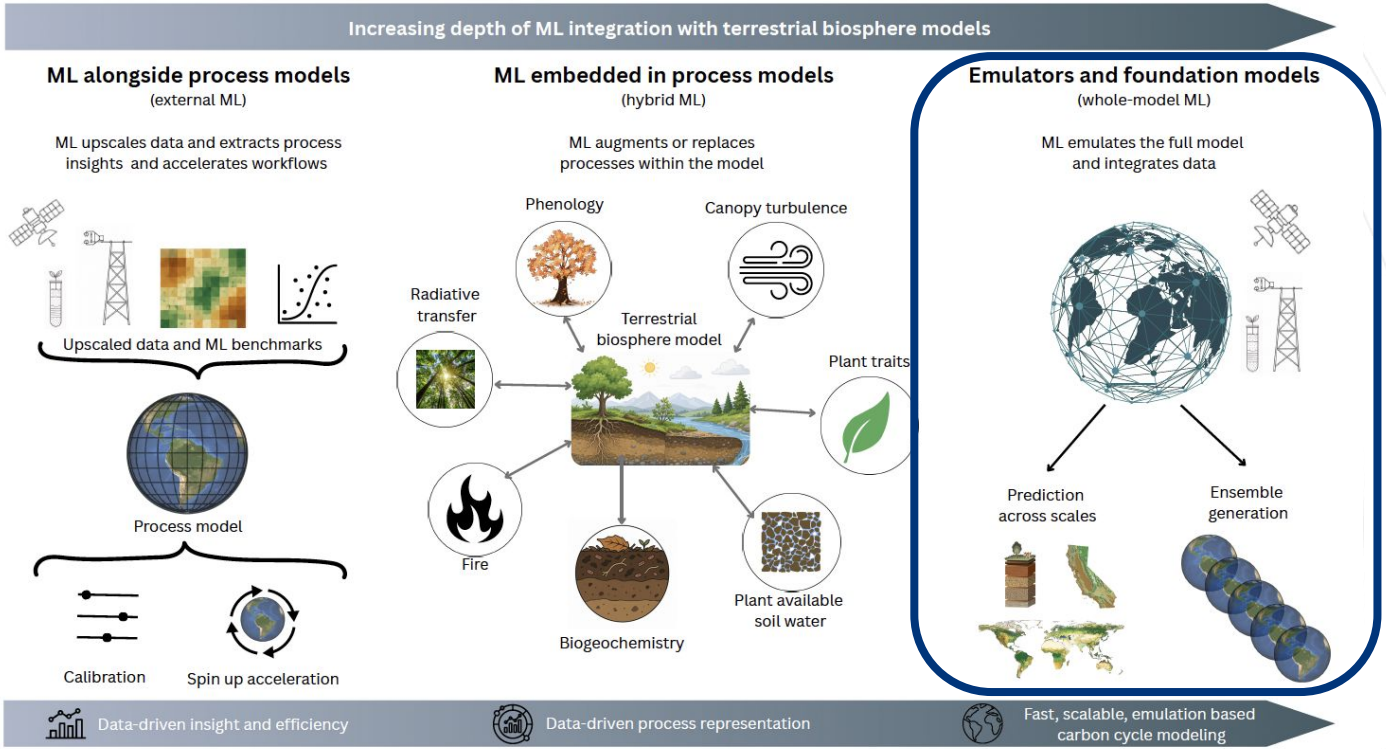


Diagram from Addisu Semie

Machine Learning for Land Modeling

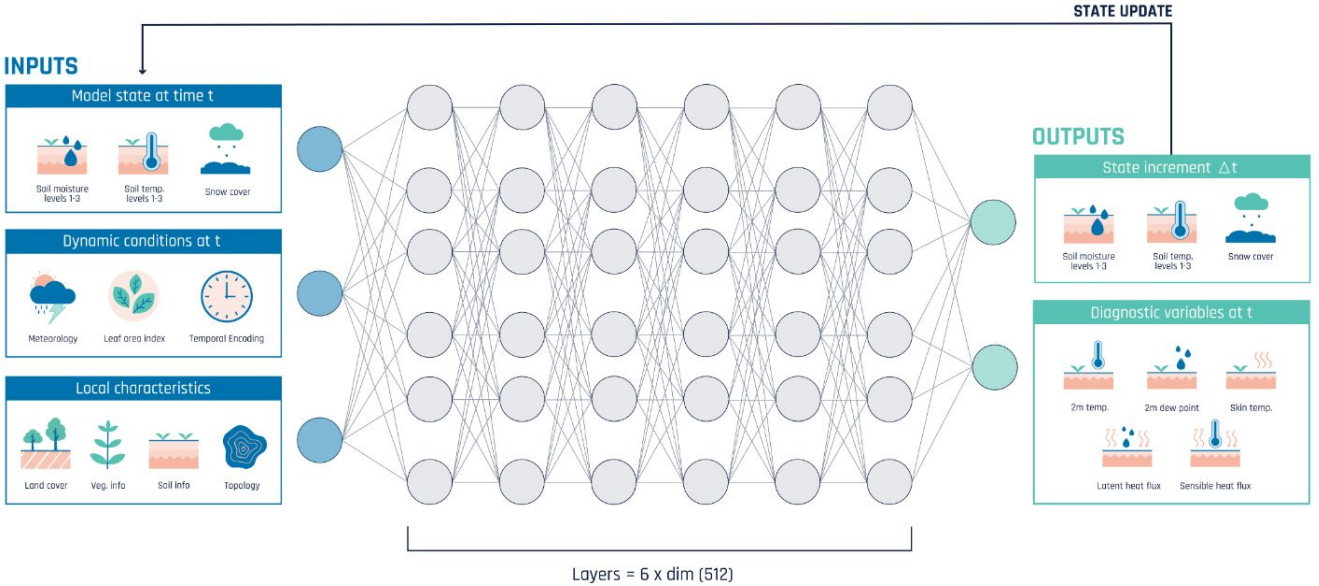


Hawkins et al., accepted

Land model emulation

aiLand, whole land model emulator for ecLand (ECMWF)





- Training on land model output to provide adequate data to learn from
- Constrained/fine-tuned by observations to avoid inheriting physical model biases

Raoult et al. (2026)

Land model emulation

subCESMulator: ML emulator for subseasonal prediction



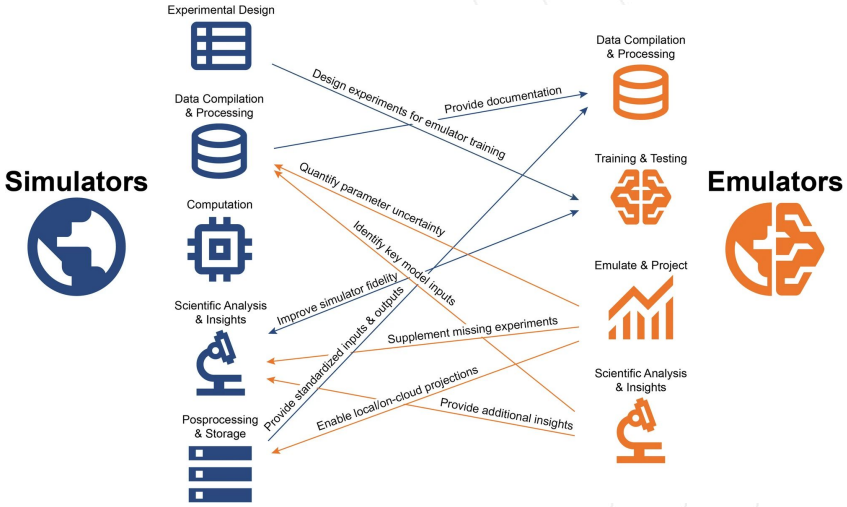
- Training on fully coupled CESM simulations with physical constraints enforced
- Integrating aspects of atmosphere, ocean/ice, land components
- What land information is important for subseasonal prediction?
    - *Soil moisture, soil temperature, snow depth, leaf area index, vegetation structure, ….*

Mayer et al., *in prep*

Land model emulation

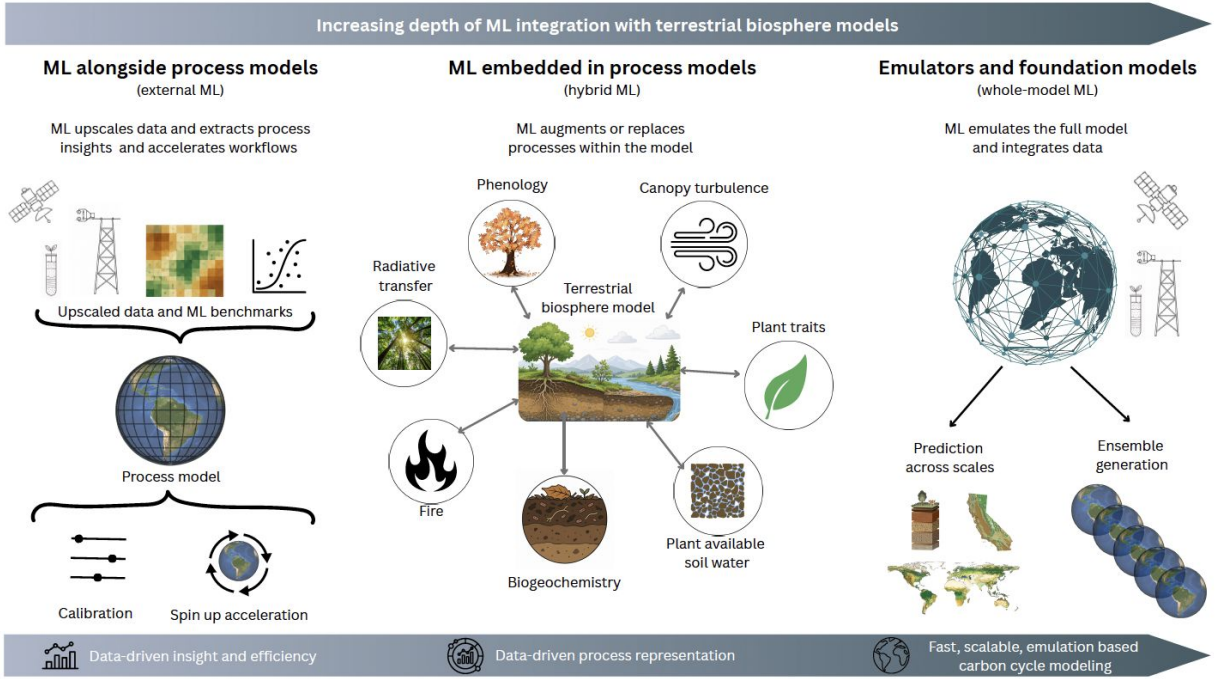
Applications:
- Prediction across scales
- Ensemble generation
- Coupling with other component emulators

Limitations:
- Extrapolation : Trained on historical data
- Interpretability : ‘Black-box’
- Scientific inquiry: predictive not explanatory



Van Katwyk et al. (2026)

Machine Learning for Land Modeling



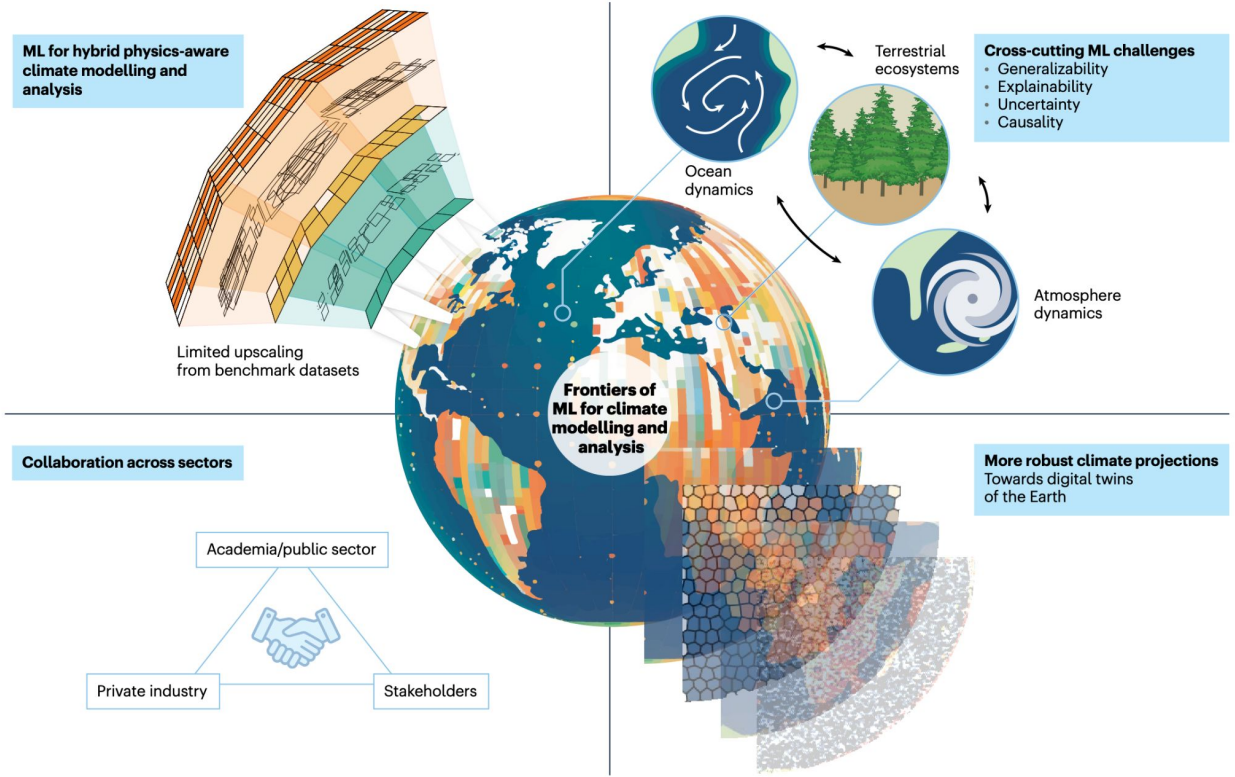
Thanks!

Questions?

lh3194@columbia.edu
kdagon@ucar.edu

Extra Slides

Machine Learning for Climate Modeling



Why ML for climate modeling?

- Enhance our ability to do science
- Make better, faster, cheaper models
- Increase accessibility to a wider community

See: Reichstein et al. (2019), Molina et al. (2023), Eyring et al. (2024a), Eyring et al. (2024b)

Machine Learning with CESM

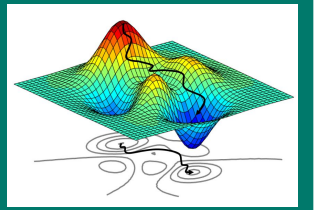
HYBRID MODELING

Incorporating ML parameterizations into CESM



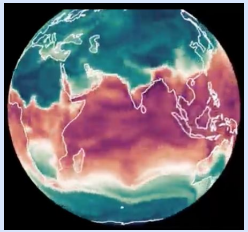
PARAMETER CALIBRATION

Calibrating CESM parameters with ML



EMULATION

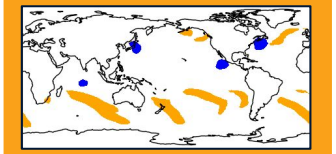
Auto-regressive emulation of CESM and component models with ML



PROCESS UNDERSTANDING

For example:

- ML-based detection of extremes
- ML-enhanced predictability



EMERGING AREAS

For example:

- AI-assisted code conversion
- AI dynamical downscaling
- Exploratory visualization with embeddings
- ML & data assimilation

...and more!

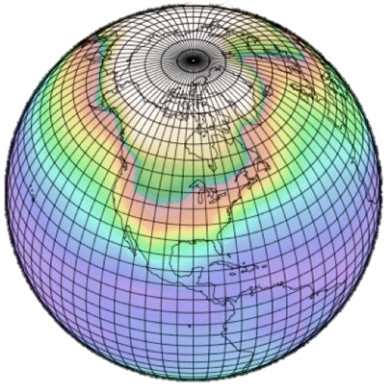
Model Calibration, or Model Tuning

PNAS PERSPECTIVE OPEN ACCESS

Are general circulation models obsolete?

V. Balaji[a,b,1], Fleur Couvreux[c], Julie Deshayes[d], Jacques Gautrais[e], Frédéric Hourdin[f], and Catherine Rio[c]

"Thus, model calibration is not a weakness of models; it, in fact, ***holds the key to how model developers learn how their model behaves****, and, consequently, how the Earth system regulates itself."*
Balaji et al., 2022 [PNAS]

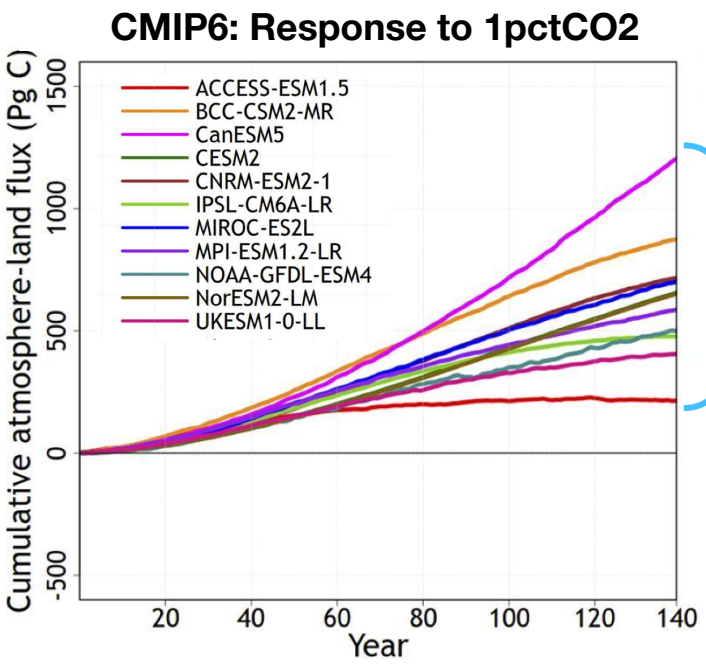


THE ART AND SCIENCE OF CLIMATE MODEL TUNING

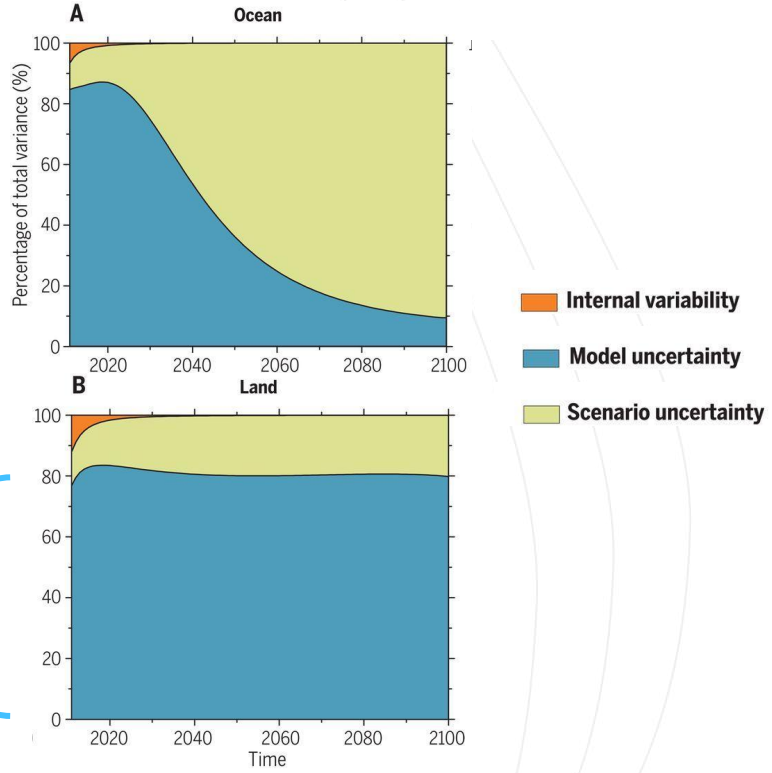
Frédéric Hourdin, Thorsten Mauritsen, Andrew Gettelman, Jean-Christophe Golaz, Venkatramani Balaji, Qingyun Duan, Doris Folini, Duoying Ji, Daniel Klocke, Yun Qian, Florian Rauser, Catherine Rio, Lorenzo Tomassini, Masahiro Watanabe, and Daniel Williamson

"As in art, there is also some ***diversity and subjectivity in the tuning process*** *because of the complexity of the climate system and because of the choices made among the equally possible representations of the system."*
Hourdin et al., 2017 [BAMS]

Carbon Cycle Uncertainty in Land Model Projections



Uncertainty in land model structure and **parameters**



Arora et al. (2020)

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

Infrastructure Development

CLM5 Parameter List

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	D	E	F	G	S	
1	name	location	min	max	References for parameter ranges	Notes
97	**Photosynthetic capacity (LUNA)**					
98	slatop	P	pft	pft	Fisher et al. 2019, Kattge et al. 2011	
99	dsladlai	P	20percent	20percent	Thornton and Zimmerman 2007	
100	jmaxb0	P	0.01	0.05		
101	jmaxb1	N	0.05	0.25		
102	wc2wjb0	P	0.5	1.5		
103	enzyme_turnover_daily	P	0.05	0.15		
104	relhExp	P	4	8		
105	minrelh	P	0.2	0.3		
106	luna_theta_cj	P	0.8	0.99		

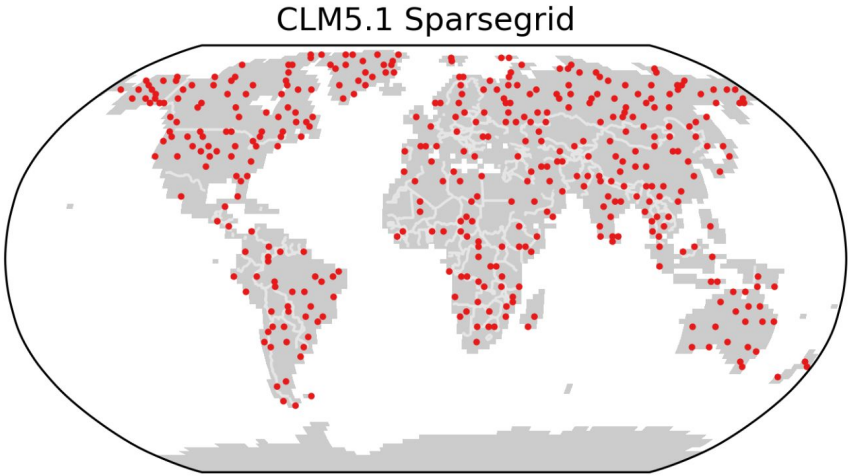
Define parameter ranges

Infrastructure Development

Land model has over 200 parameters!
How* do we sample all of them?*

200 parameters x 2 bounds (high/low values)
x 6 environmental perturbations
= **2400 simulations**

- Utilize a “sparsegrid”: 400 representative gridcells based on k-means clustering *(Hoffman et al. 2013)*
- Leverage a matrix representation of model biogeochemistry to reduce spin-up time *(Lu et al. 2020)*



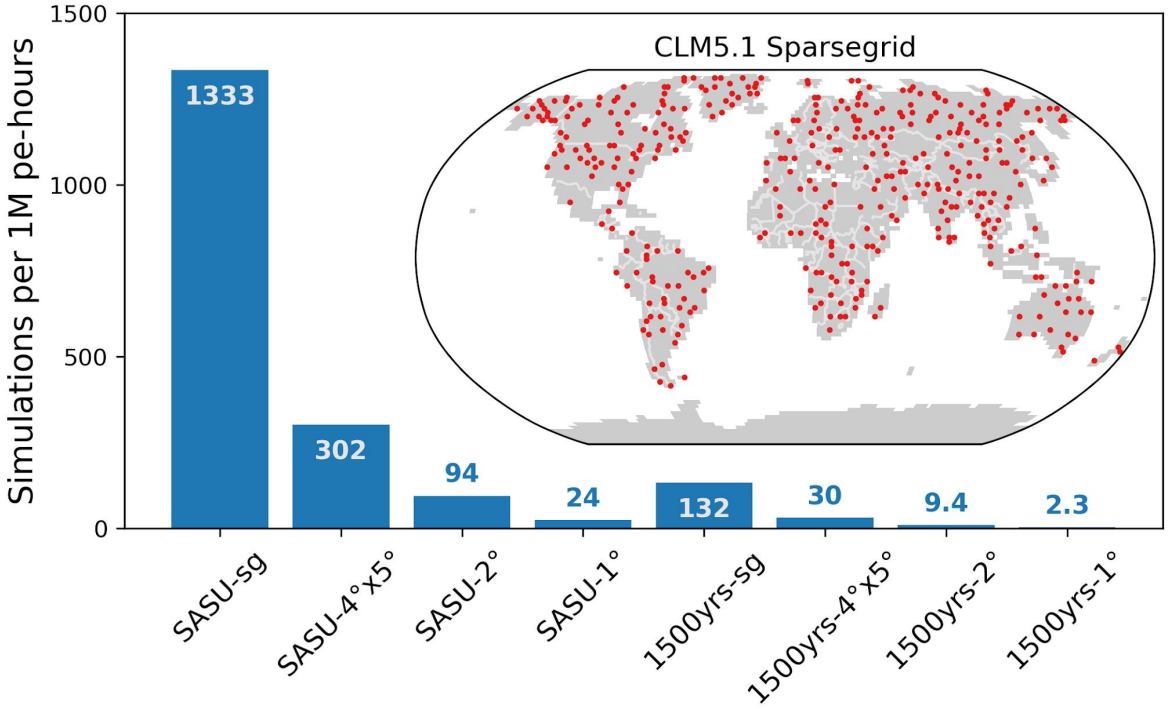




Increase computational efficiency

Kennedy et al. (2025)

Computational Efficiency



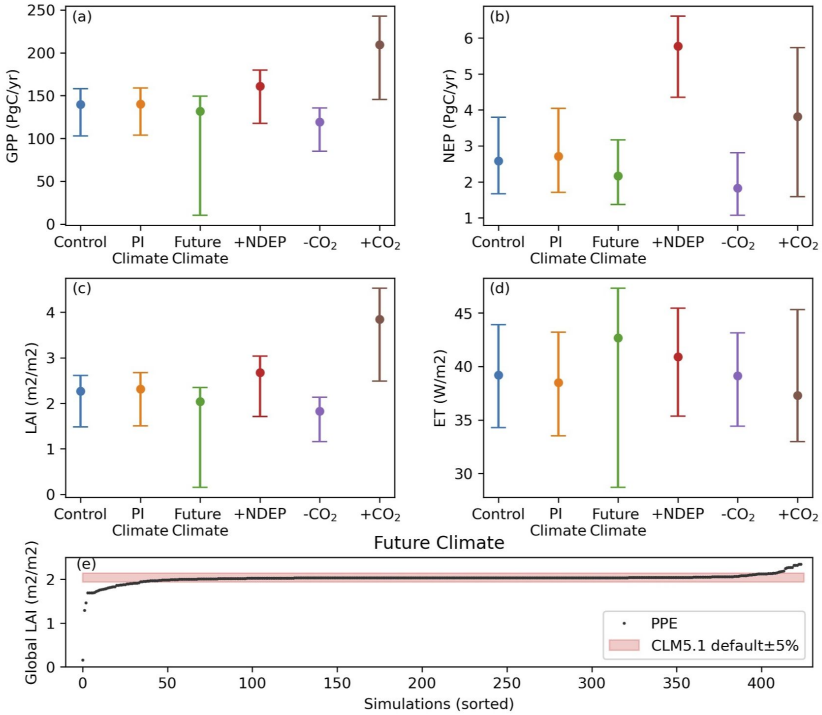
Kennedy et al. (2025)

CLM5/6 Perturbed Parameter Ensembles

Table 2
In Total, 211 Parameters Were Perturbed in This Experiment

Parameter	Description	Model domain	Varies by PFT?
cv	Turbulent transfer coefficient	Sensible, latent heat and momentum fluxes	
dleaf	Leaf characteristic length	Sensible, latent heat and momentum fluxes	yes
d_max	Dry surface layer (DSL) parameter	Sensible, latent heat and momentum fluxes	
frac_sat_soil_dsl_init	Fraction of saturated soil at which DSL initiates	Sensible, latent heat and momentum fluxes	
fff	Decay factor for fractional saturated area	Hydrology	
liq_canopy_storage_scalar	Canopy-storage-of-liquid-water parameter	Hydrology	
maximum_leaf_wetted_fraction	Maximum leaf wetted fraction	Hydrology	
sand_pf	Perturbation factor for sand content of soil column	Hydrology	
sucsat_sf	Scale factor for minimum soil water potential	Hydrology	
medlynintercept	Medlyn intercept of conductance-photosynthesis relationship	Stomatal resistance and photosynthesis	yes
medlynslope	Medlyn slope of conductance-photosynthesis relationship	Stomatal resistance and photosynthesis	yes
tpu25ratio	Ratio of tpu25top to vcmax25top	Stomatal resistance and photosynthesis	
jmaxb0	Baseline proportion of nitrogen allocated for electron transport	Photosynthetic capacity	
jmaxb1	Response of electron transport rate to light	Photosynthetic capacity	
slatop	Specific leaf area at top of canopy	Photosynthetic capacity	yes
theta_cj	Empirical curvature parameter for photosynthesis colimitation	Photosynthetic capacity	yes
wc2wjb0	Baseline ratio of wc:wj	Photosynthetic capacity	
FUN_fracfixers	fraction of carbon available for N fixation	Fixation and uptake of Nitrogen	yes
KCN	Nitrogen acquisition parameter group	Fixation and uptake of Nitrogen	yes
kmax	Plant segment max conductance	Plant hydraulics	yes
krmax	Root segment max conductance	Plant hydraulics	yes
psi50	Water potential at 50% loss of conductance	Plant hydraulics	yes
nstem	Stem number	Biomass heat storage	yes
lmr_intercept_atkin	Intercept in the calculation of leaf maintenance respiration	Plant respiration	yes
froot_leaf	Allocation parameter: new fine root C per new leaf C	Carbon and nitrogen allocation	yes
leafcn	Leaf C:N	Carbon and nitrogen allocation	yes
leaf_long	Leaf longevity	Vegetation phenology and turnover	yes
cpha	Activation energy for cp	Acclimation parameters	
jmaxhd	Deactivation energy for jmax	Acclimation parameters	
kcha	Activation energy for kc	Acclimation parameters	
lmrha	Activation energy for lmr	Acclimation parameters	
lmrhd	Deactivation energy for lmr	Acclimation parameters	
tpuha	Activation energy for tpu	Acclimation parameters	
tpuse_sf	Scale factor for tpu entropy term	Acclimation parameters	
vcmaxha	Activation energy for vcmax	Acclimation parameters	
vcmaxhd	Deactivation energy for vcmax	Acclimation parameters	

Note. These are the parameters mentioned within the main text. A complete set of parameters, with ranges, is included in a spreadsheet in Supporting Information S1.



Dagon et al. 2020, Kennedy et al. 2025, Foster et al. 2026, Hawkins et al. *in prep*

Systematic Parameter Calibration with ML

Can we develop a systematic parameter calibration workflow **leveraging machine learning?**

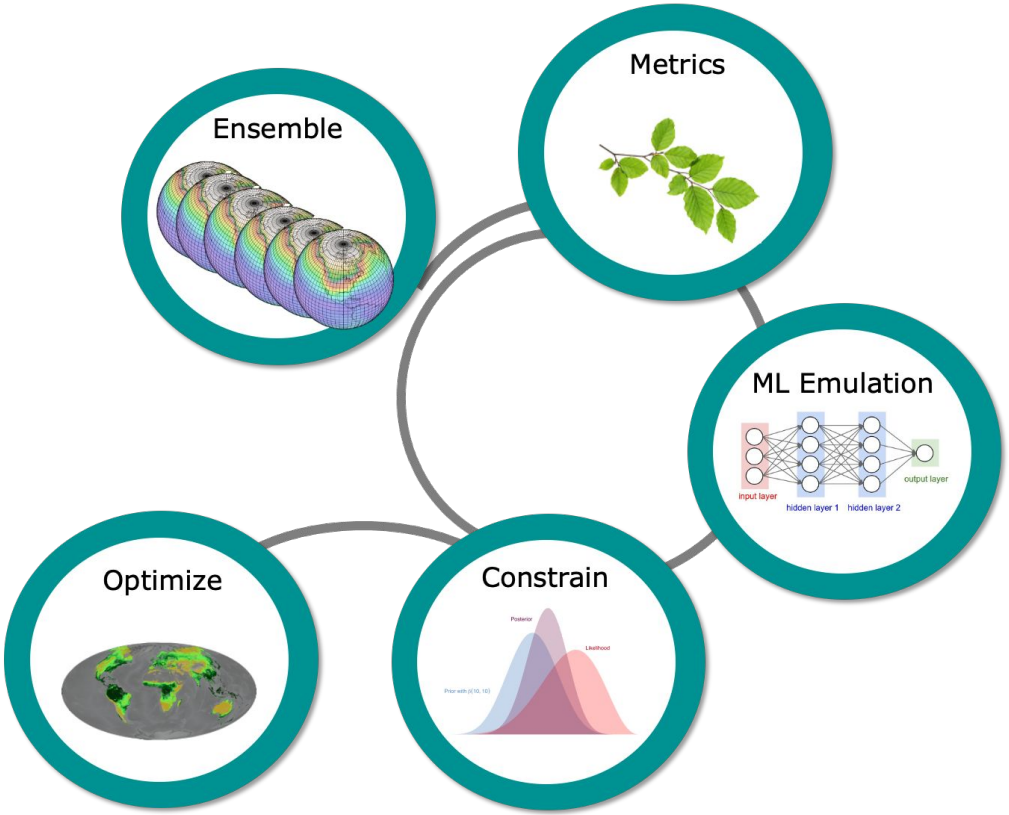


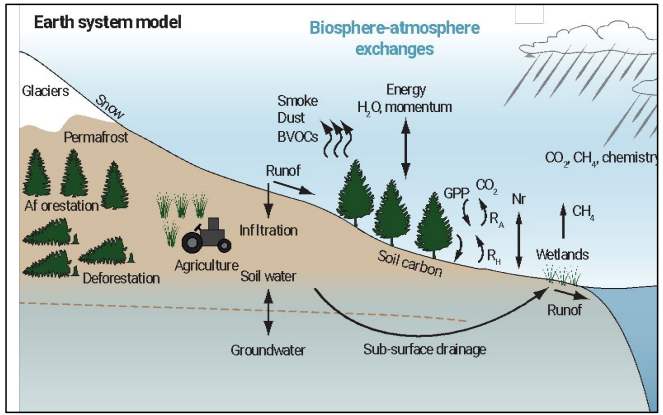
Figure from Linnia Hawkins

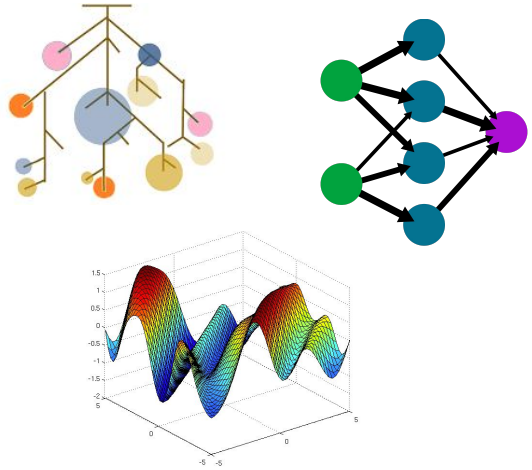
Training the Emulators

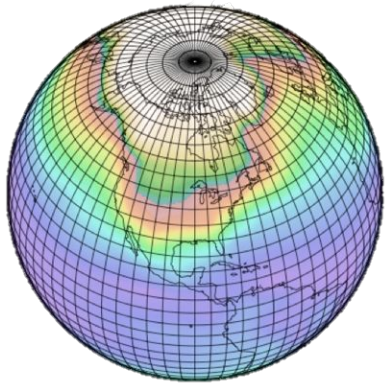
Input: CESM **parameter values** used to generate a perturbed parameter ensemble (PPE)

Machine learning emulator *(e.g., neural network (NN), random forest, gaussian process (GP))*

Output: **variable/metric** of interest from the PPE simulation output



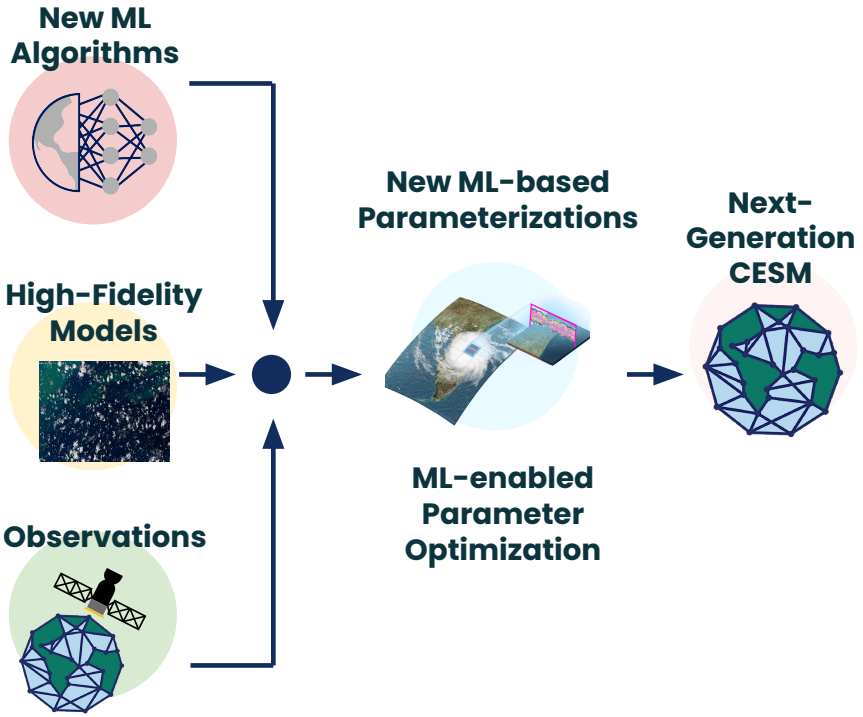




Learning the parameter response functions

CLM5: Dagon et al. (2020), Kennedy et al. (2025); CLM6: Hawkins et al. *in prep*
CAM6: Eidhammer et al. (2024); CAM7 tuning uses method from Larson et al. (2025)

Towards a machine learning enhanced version of the Community Earth System Model (CESM3-MLe)



Learning the Earth with Artificial intelligence and Physics NSF Science and Technology Center

LEAP

M²LInES Schmidt Sciences

M2LInES

Harness new ML + data to enhance CESM

Parameterizations in Development for CESM3-MLe

LEAP

M^{2}LInES

Other

Radiation

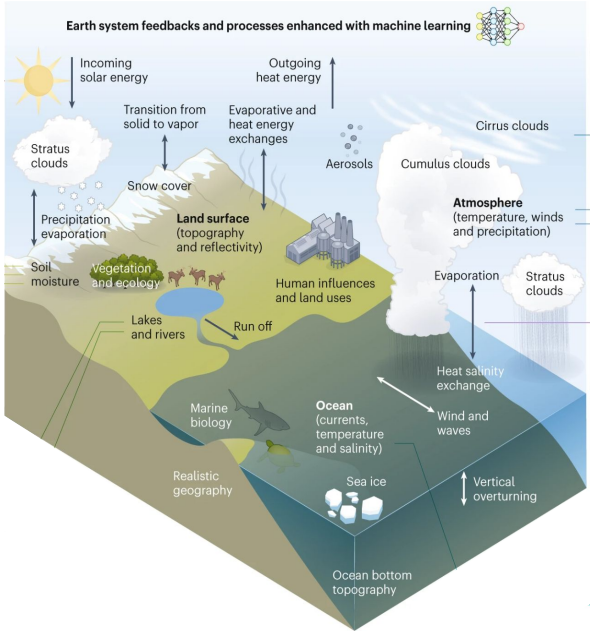
Phenology

Pedotransfer functions

Sea ice heat conduction

Ice sheet friction

Sea ice floe perimeter



Gravity Waves

Warm rain microphysics

Ice microphysics

Convection

Convective triggering

Cloud cover

Vertical Mixing (KPP)

Ocean Mesoscales

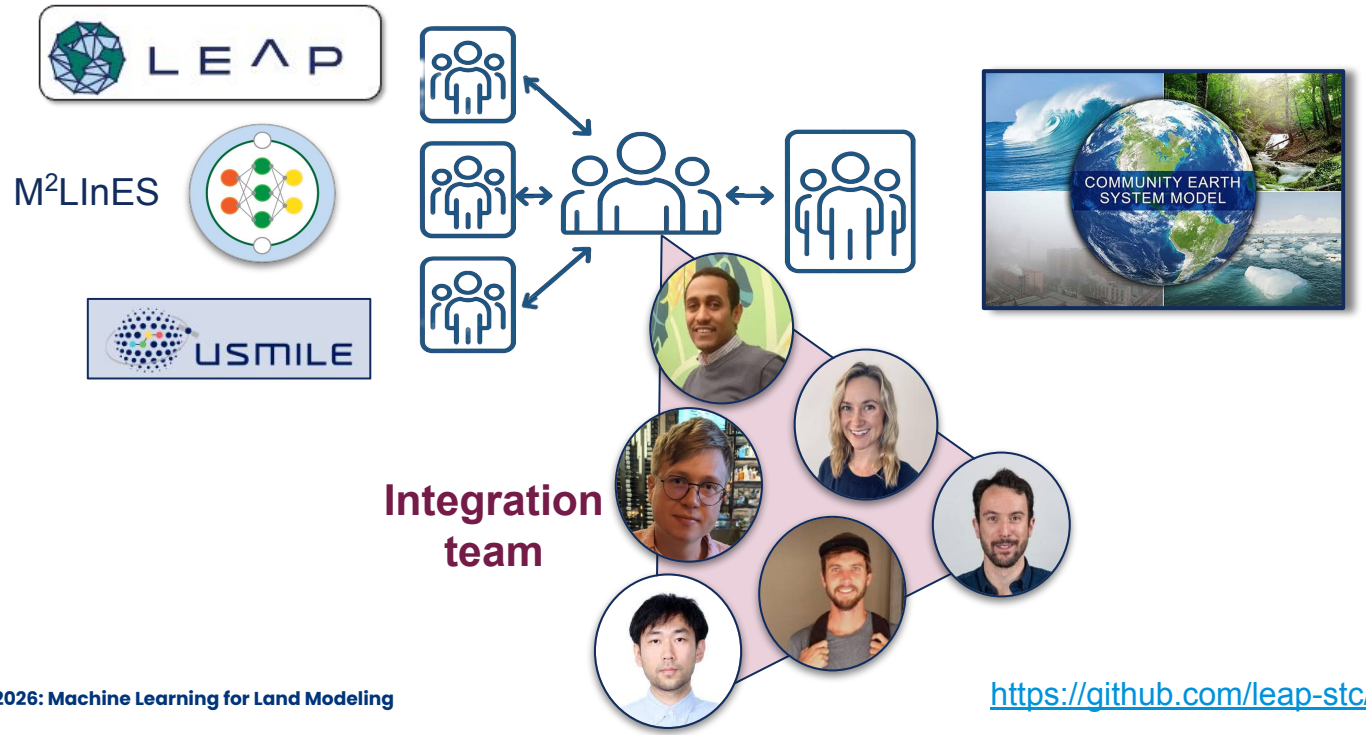
Air-sea turbulent fluxes

Figure modified from Eyring et al. 2024

Implementation of ML-based Parameterizations

Build robust, flexible, and sustained interactions between ML projects and CESM scientists and developers.

Make it easy for anyone who want to test ML-parameterizations in CESM.



https://github.com/leap-stc/Integration_team

Towards a machine learning enhanced version of the Community Earth System Model (CESM3-MLe)



Learning the Earth with Artificial intelligence and Physics NSF Science and Technology Center



M²LInES Schmidt Sciences

Defining success

- Several ML-based parameterizations integrated into CESM (1–3 in atm, ocn, lnd, sea/land ice)
- ML-based parameter calibration
- Reduced biases in critical fields, especially extremes
- Community platform and shared resources for exploring ML in CESM

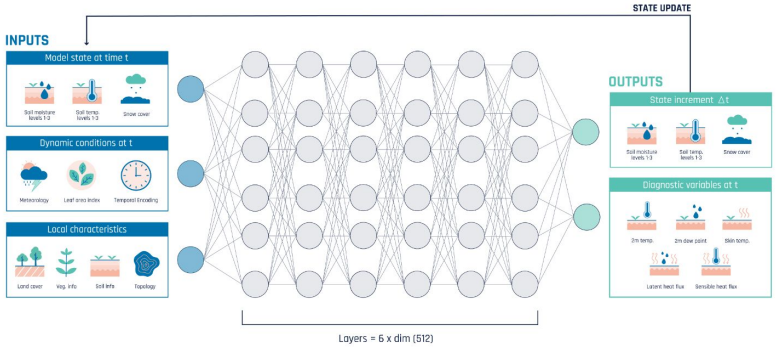
Anticipated challenges

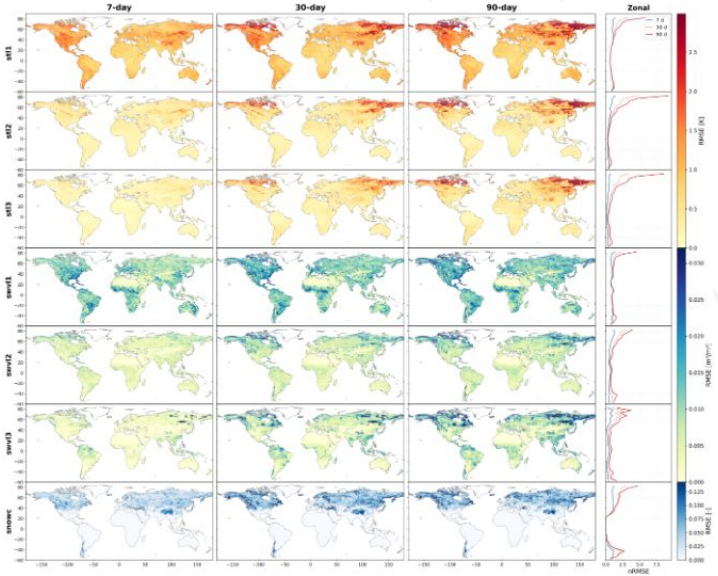
- Are ML parameterizations reliable in out-of-training climates?
- Where do unanticipated interdependencies emerge?
- Substantially new simulated climate that may degrade orthogonal aspects of simulation
- New tuning challenges with some tuning knobs removed

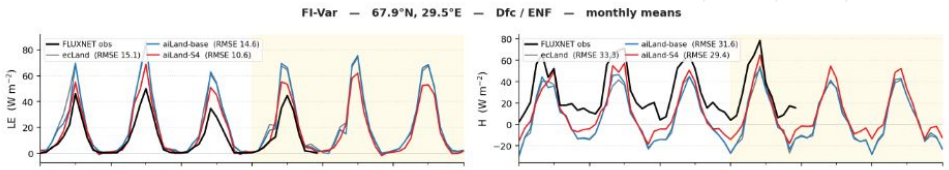
Slide adapted from Dave Lawrence

Land model emulation

aiLand, Raoult et al., In review GMD



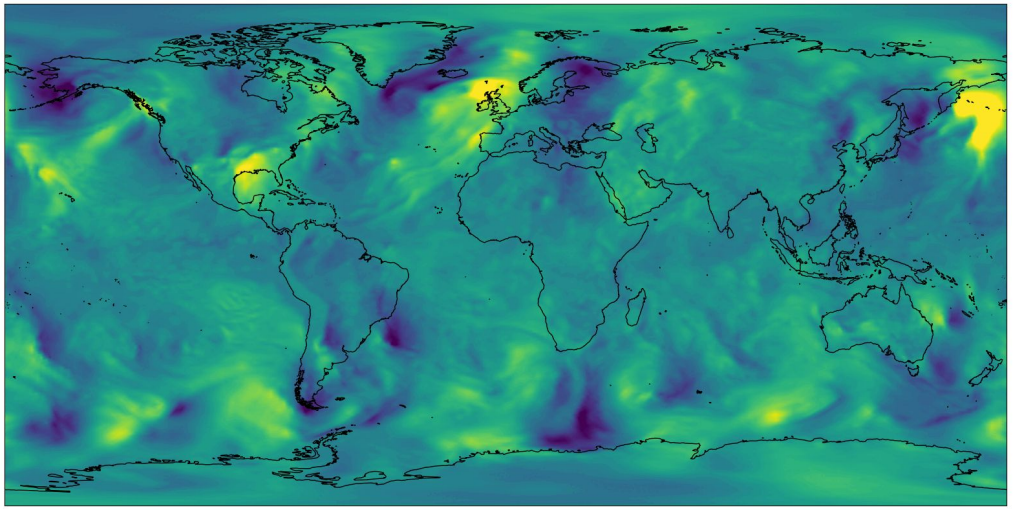




Raoult et al., in review

Climate Model Emulation

- Build on success of AI for numerical weather prediction
- Accelerate climate simulations
- Generate large projection ensembles
- Better capture internal variability and extreme events



Animation shows a 10-day forecast of meridional wind at 850 hPa using ECMWF's Artificial Intelligence Forecasting System (AIFS). *Source:* ECMWF

CREDIT: Community Research Earth Digital Intelligence Twin

What is CREDIT?
An open, Python-based, foundational platform for conducting research with **AI Earth System Models** (aka *emulators*). [Schreck, et al. 2025]

CREDIT enables users to

- Load large datasets.
- Train customizable AI models at scale.
- Incorporate physical constraints and transforms
- Deploy models for forecasting, hindcasting, or projections.

CREDIT's full pipeline is **open source** and is being **openly developed**.



https://github.com/NCAR/miles-credit