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

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Next-generation Earth System modeling

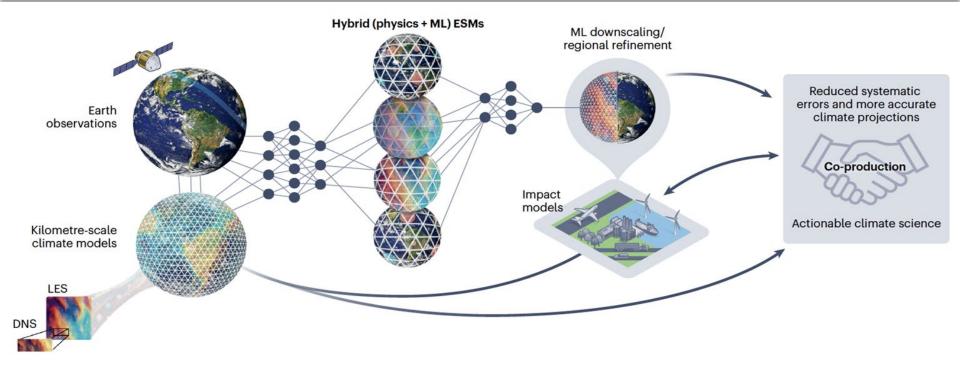


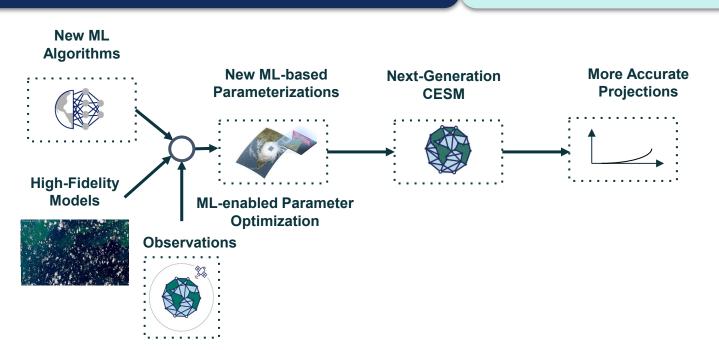
Figure from Eyring, Gentine, Camp&/alls, Lawrence, Reichstein (Nature Climate Change, 2024)





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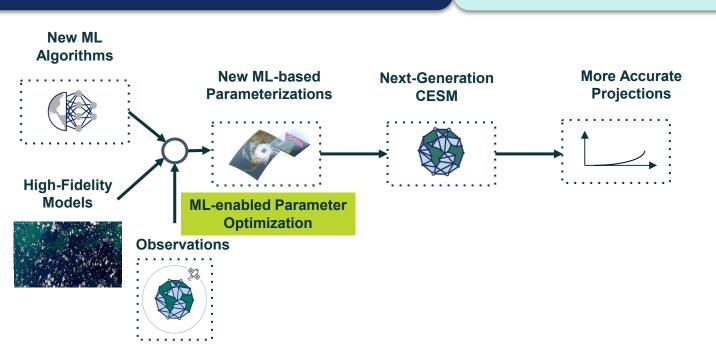






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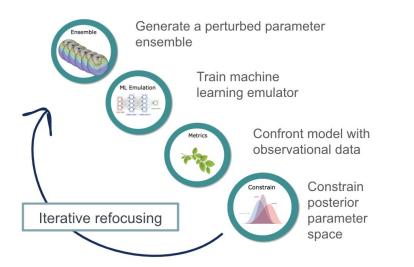
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LEAP Phase 1: Parameter estimation methodologies have been developed for land (CLM) and atmosphere (CAM) model components

CLM

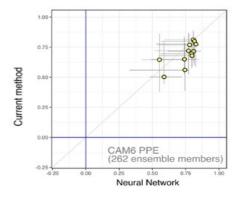


Linnia Hawkins, Daniel Kennedy, Katie Dagon, Dave Lawrence

CAM

Additive Gaussian Process Emulator Designed for sparse state spaces:

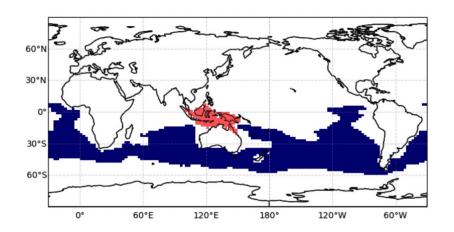
- Additive and simple
- Parameter interaction considered
- Less likely to overfit

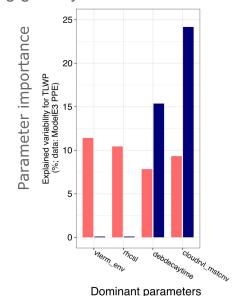


Qingyuan Yang, Greg Elsaesser, Brian Medeiros, Addisu Semie, Marcus van Lier-Walqui



Insight: Individually insensitive parameters can be cumulatively important
Why? Some parameters are only locally/regionally sensitive
Therefore: Emulating only global climatologies may not be sufficient for all problems
Implication: May be able to both decrease local biases while still calibrating globally

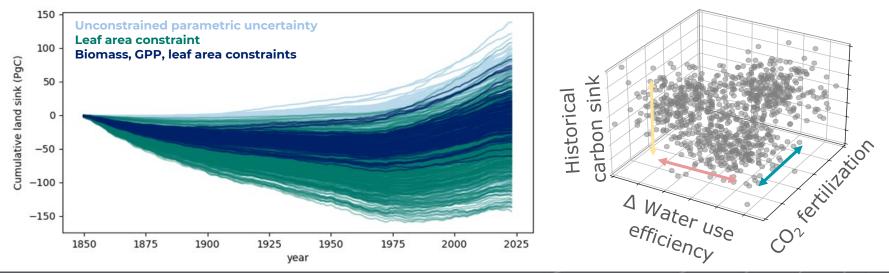






CLM PPE activities

- Calibrate CLM6 for CESM3
- Publish an observationally constrained perturbed parameter ensemble
- Constrain / understand land carbon cycle uncertainty
- For a possible future CESM3 large ensemble (emissions-driven mode), utilize carefully selected parameter sets that span unconstrained emergent behavior in land carbon cycle and ECS or TCR







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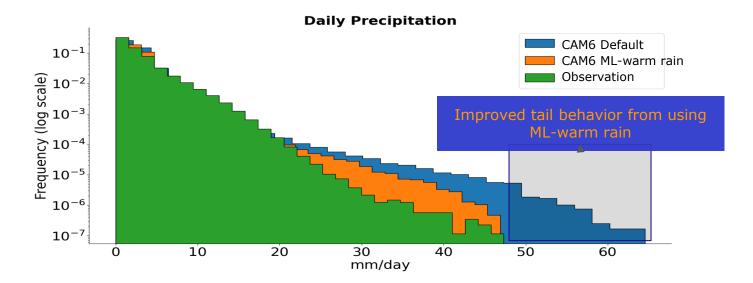
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LEAP Phase 1: Demonstrate pathway and impact of ML-based parameterizations in CESM

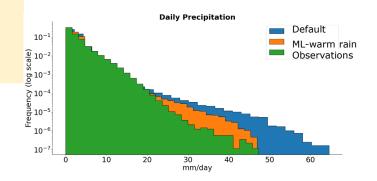
Warm rain microphysics: Emulate cloud droplet autoconversion and accretion with NNs trained on CAM simulations with warm rain process replaced with highly resolved bin microphysics (TAU code)



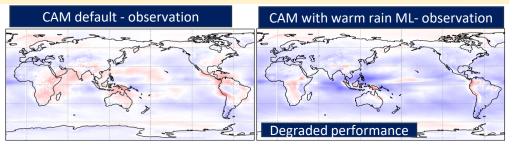


Developing workflow to recalibrate after ML paramaterizations implemented

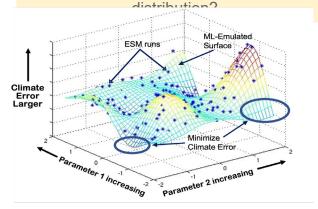
1. ML warm rain microphysics → improvement in rainfall distribution



2. But, degraded performance for other fields is likely with new parameterization



3. Using ML for auto-tuning, can we recalibrate CAM to correct the degraded performance, while simultaneously retaining the improvement in rainfall



Schematic only; representative of a climatological radiation or cloud field



Slide from Qingyuan Yang and Greg Elsaesser

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

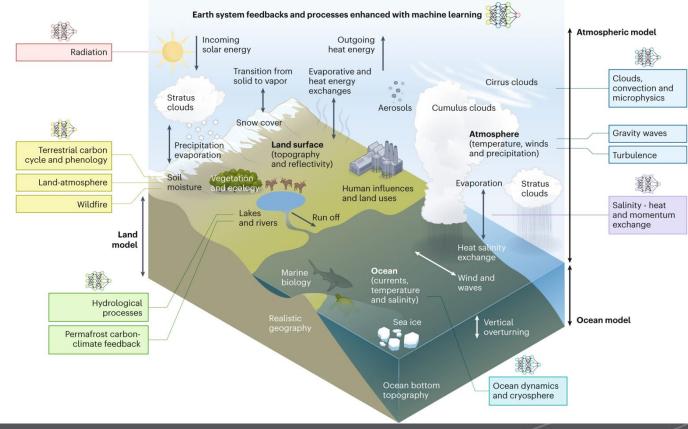
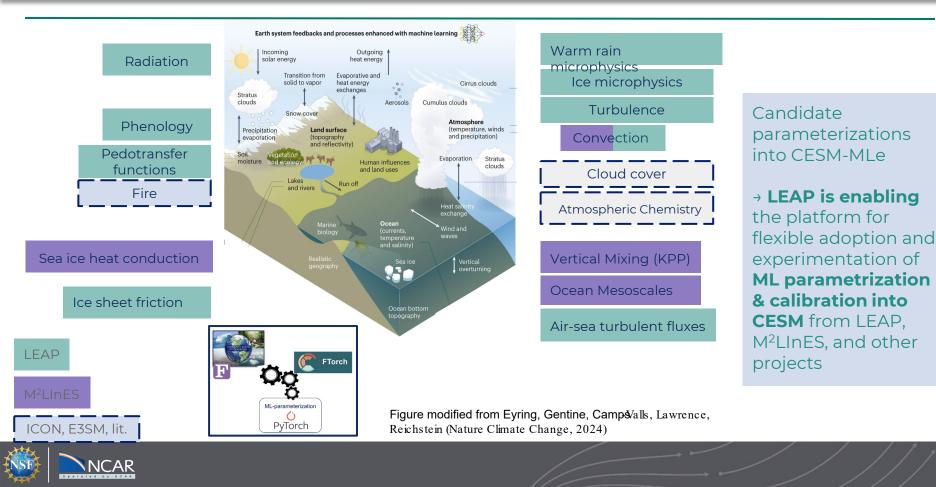






Figure from Eyring, Gentine, Camps-Valls, Lawrence, Reichstein (Nature Climate Change, 2024)

Candidate parameterizations and tools for CESM3-MLe



Identified need

More productive and sustained interactions between LEAP and M²LInES projects and CESM scientists and developers



Identified need

More productive and sustained interactions between LEAP and M²LInES projects and CESM scientists and developers





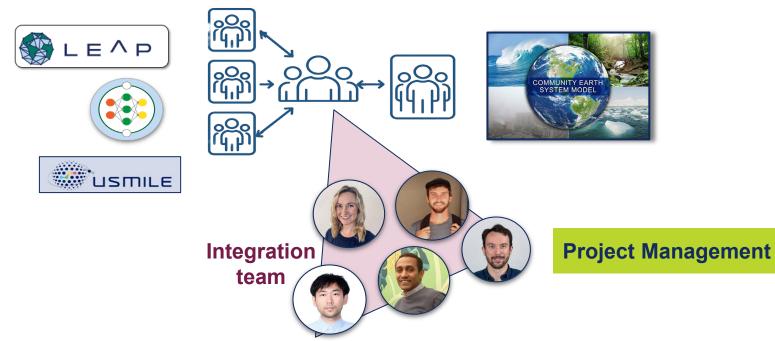




github.com/leap-stc/Integration_team

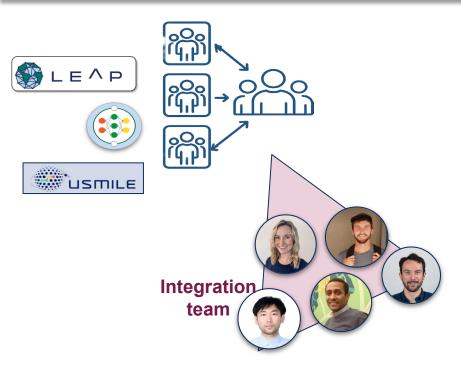
Identified need

More productive and sustained interactions between LEAP and M²LInES projects and CESM scientists and developers





github.com/leap-stc/Integration_team



CESM Integration Survey (selected questions)

- Which physical process is your ML model targeting?
- How well do your inputs/outputs align with those available in the CESM component model?
- What dataset(s) are being used for training?
- How are you currently testing your ML parameterization?
- How will you test in a CESM-relevant context?
- What is the planned mechanism for integrating your ML model into CESM?
- Are there intermediate calculations or dependencies that must be implemented within CESM?
- Will the ML parameterization require additional tuning once integrated into CESM?
- What additional support or collaboration would help facilitate your model's integration into CESM?
- Are there any anticipated concerns or risks regarding your ML parameterization's integration into CESM?



github.com/leap-stc/Integration team

Towards a Machine-Learning enhanced CESM (CESM3MLe)



Defining Success for CESM3-MLe

- Several ML-based parameterizations into CESM (1-2 atm, 1-2 ocn, 1-2 Ind, 1 sea ice/land ice)
- ML parameter calibration (Ind, atm)
- Reduced biases in critical fields, especially extremes

Push forward over next 18-24 months to test the hypothesis that ML can help build better and more accurate ESMs

- Sustained team interactions (e.g., PI, ML-param developer, experienced CESM developer, and SE)
- More coordination / communication (github CESM-MLe project management, development meetings)

Anticipate that there will be challenges

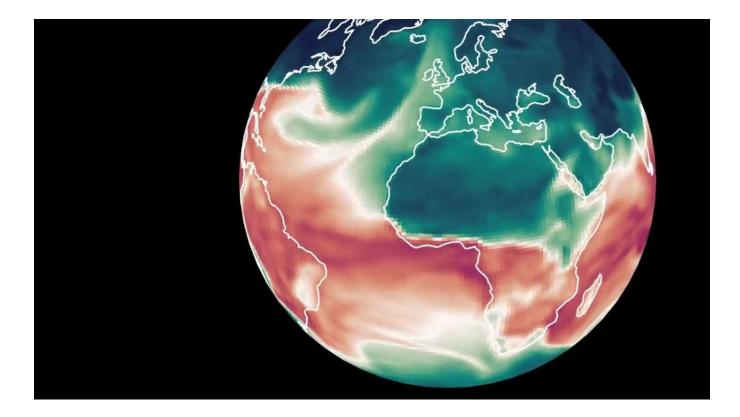
• ML parameterizations in out-oftraining climates



- CESM model instabilities with new ML
- Unanticipated interdependencies
- Substantially new simulated climate that may degrade orthogonal aspects of simulation
- New tuning challenges with some tuning knobs removed



CAMulator (CREDIT):





Looking Forward with CREDIT / CESMulator

- Coupling to a dynamic ocean / land (Chapman, Lauritzen)
- Radiative forcing experiments / CESM future climate (Chapman)
- CESMulator S2S initialized forecast system (Mayer, Chapman)
- Emulating CLM (Hawkins)
- Diffusion based post-processing (CISL + CGD)
- Near Real Time forecasts (CISL + CGD)
- Ensemble Capabilities (CISL + CGD)

(An) idea is to include CAMulator along with CREDIT platform within the CESM3 release as a supported research tool



Next-generation Earth System modeling

