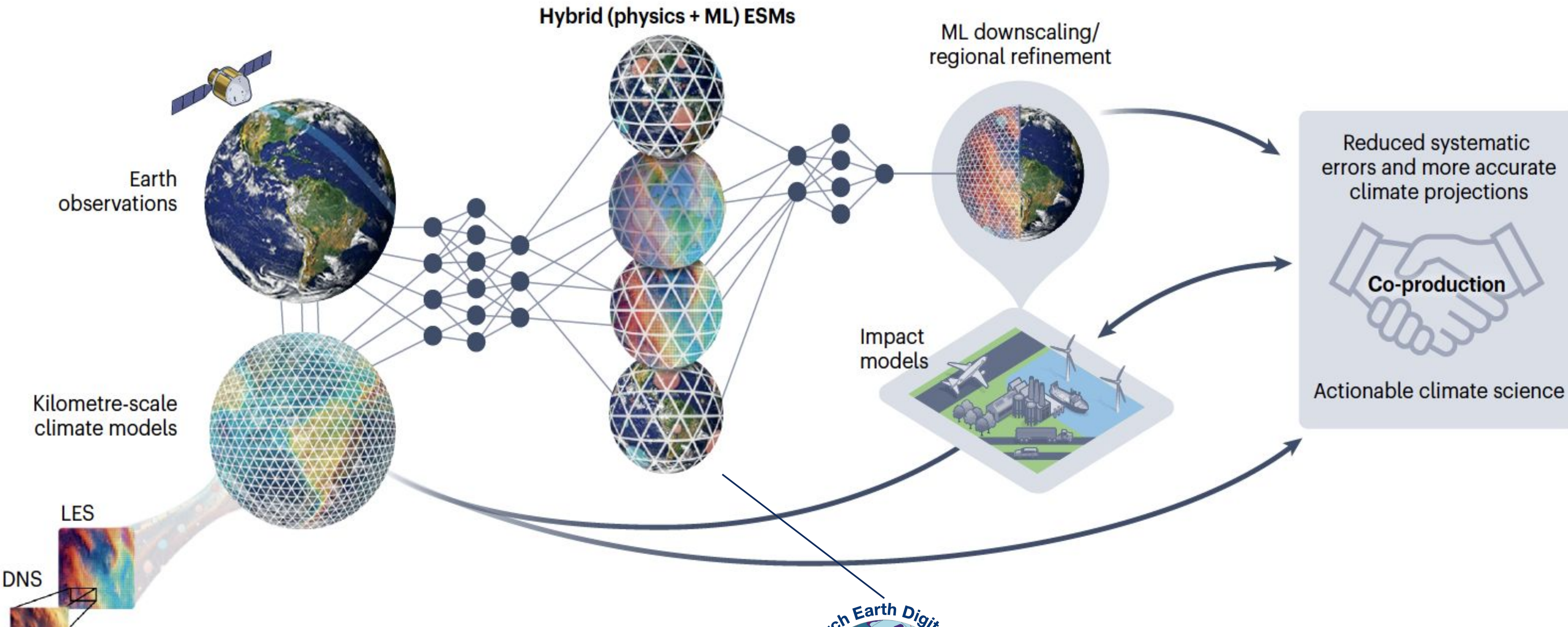
Towards a machine learning enhanced version of the Community Earth System Model (CESM3-MLe)

Exploiting AI/ML across CESM Activity

David Lawrence
CESM Chief Scientist
LEAP Model Development Liaison

FUTURE

AI/ML can help build next-generation Earth System modeling frameworks



Community Research Earth Digital Intelligence Twin

CREDIT is a machine learning-based research platform for training and operating AI autoregressive models

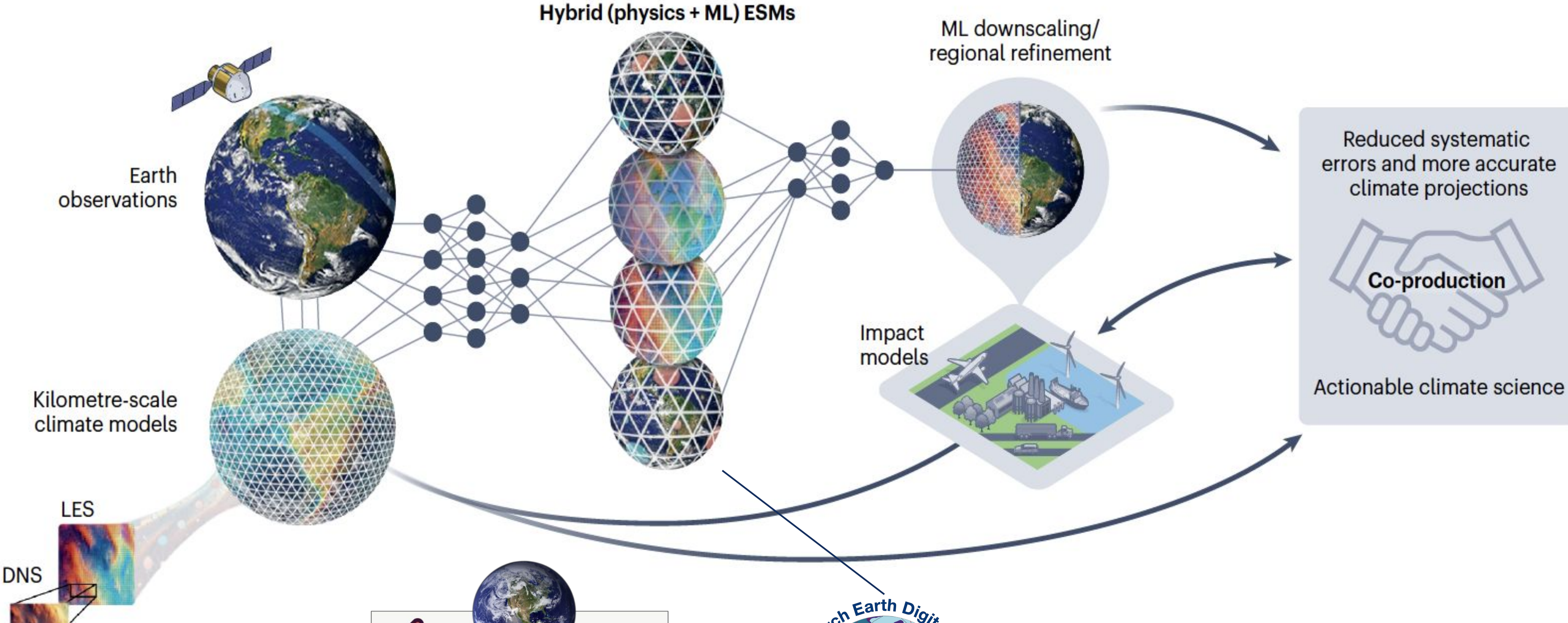
Figure from Eyring, Gentine, Camps-Valls, Lawrence, Reichstein (Nature Climate Change, 2024)

Earth System Models are also virtual laboratories

Virtual laboratory to study

- Earth system variability and change
- Earth system predictability
- Weather from local to global scales
- Biogeochemical cycles
- Air quality
- Space weather
- Ice sheet - climate interactions
- Hydrological cycles
- Ecological change
- Processes and process interactions
- Land-atmosphere (physical, chemical) interactions
- Ocean-sea ice-atmosphere interactions
- …

AI/ML can help build next-generation Earth System modeling frameworks



Community Research Earth Digital Intelligence Twin

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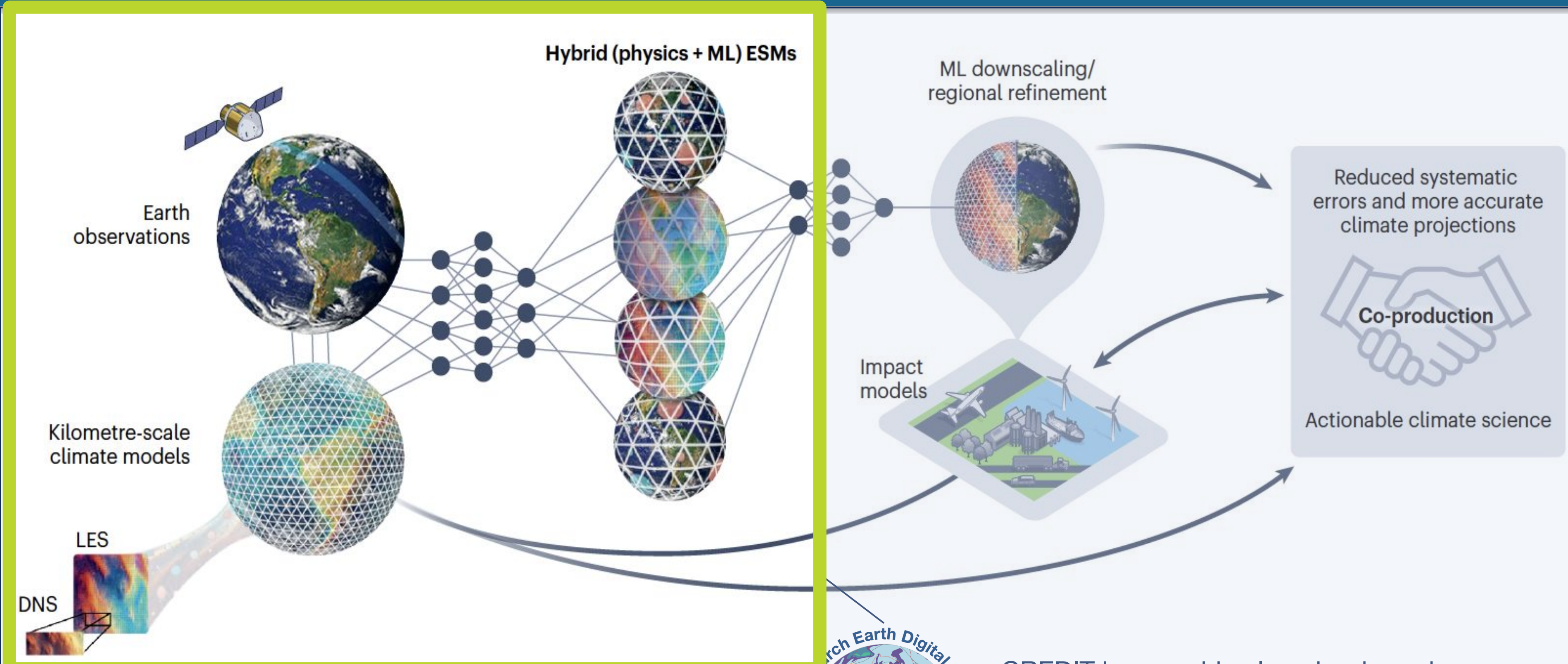
AI/ML can help build next-generation Earth System modeling frameworks



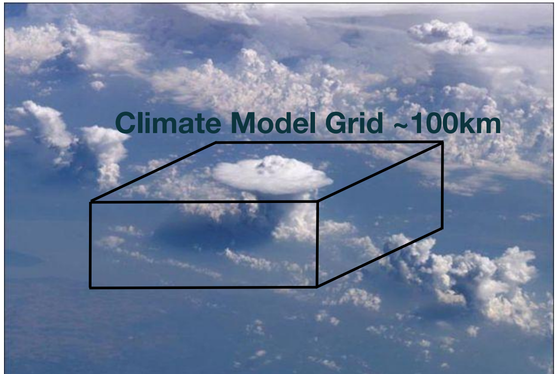
CREDIT is a machine learning-based research platform for training and operating AI autoregressive models

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

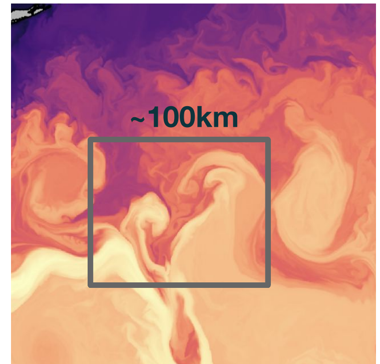
Unresolved Small + Complex Processes Require "Parameterizations" which drive projection uncertainties

Physical
+
Biological
Processes

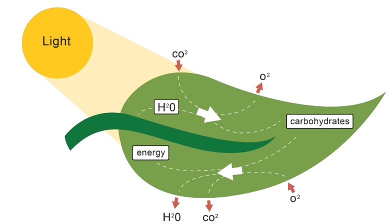
Clouds

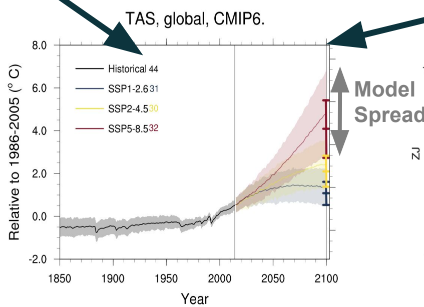


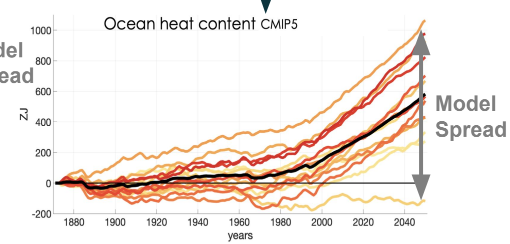
Ocean Eddies

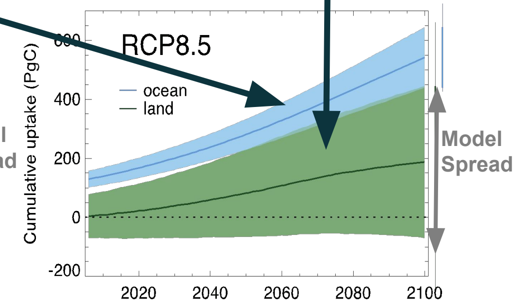


Photosynthesis





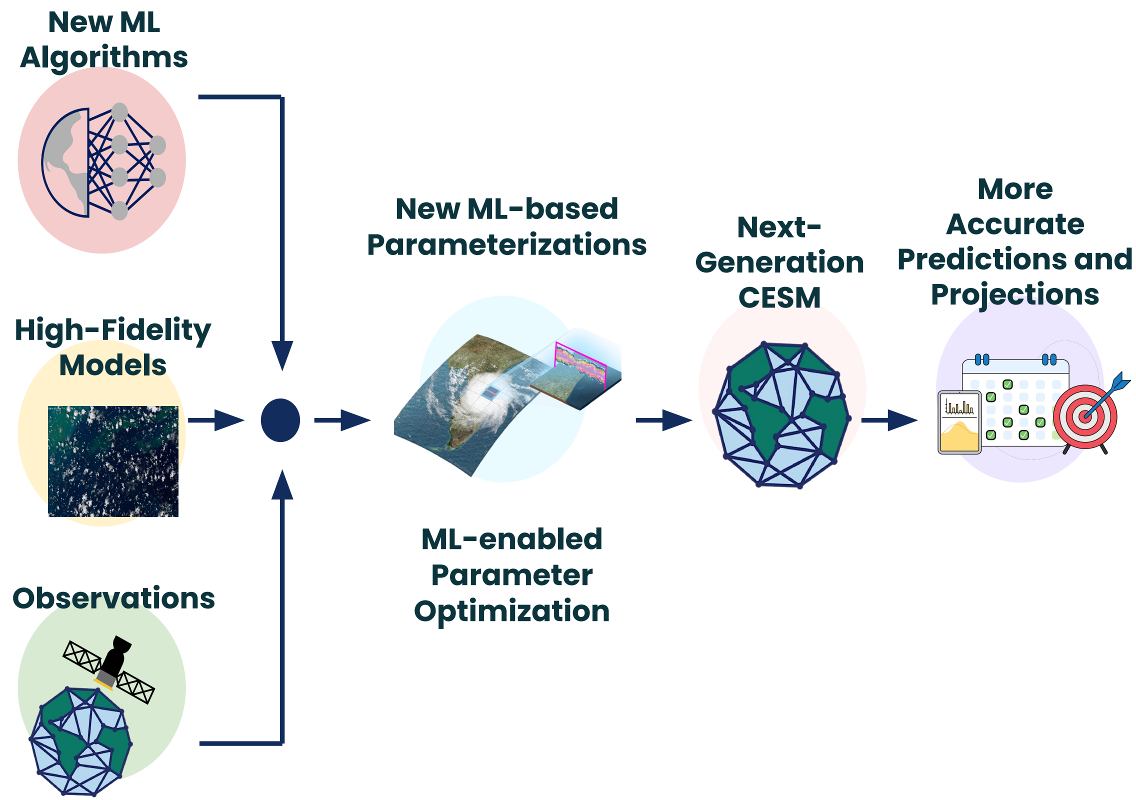




- Model errors dominate (>50%) uncertainties <40 years

Gentine et al., 2018 *Geo Res Lett*, Newsom, Zanna et al., 2020 *Geo Res Lett*; Bronselaer + Zanna, 2020 *Nature*; Friedlingstein et al. 2006 *J Climate*

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



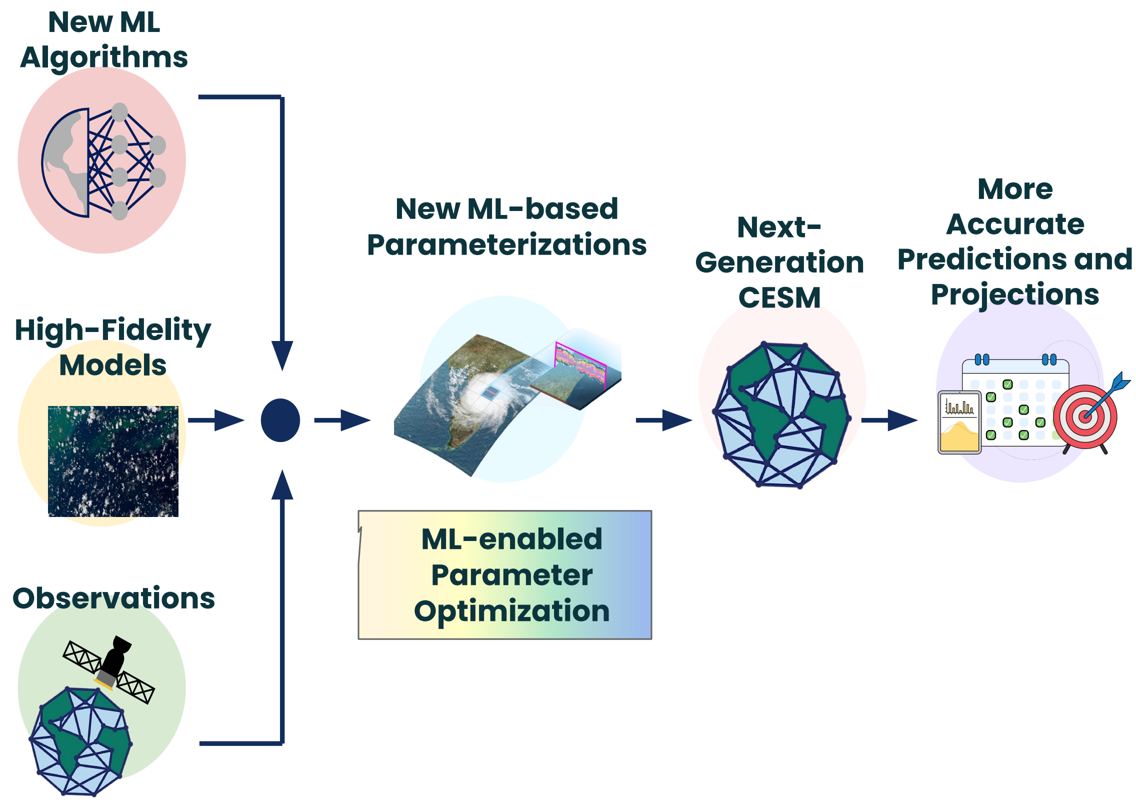
L E Λ P
Learning the Earth with Artificial intelligence and Physics NSF Science and Technology Center

M²LInES Schmidt Sciences

Harness new ML + data to transform CESM

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

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

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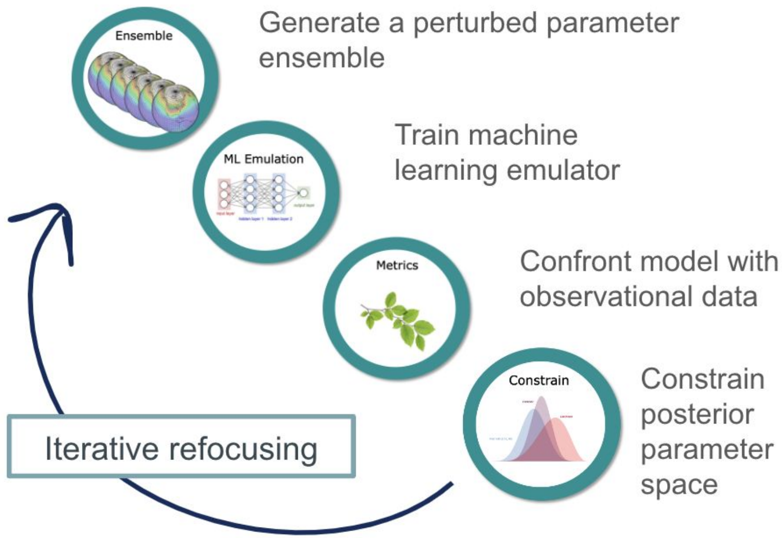
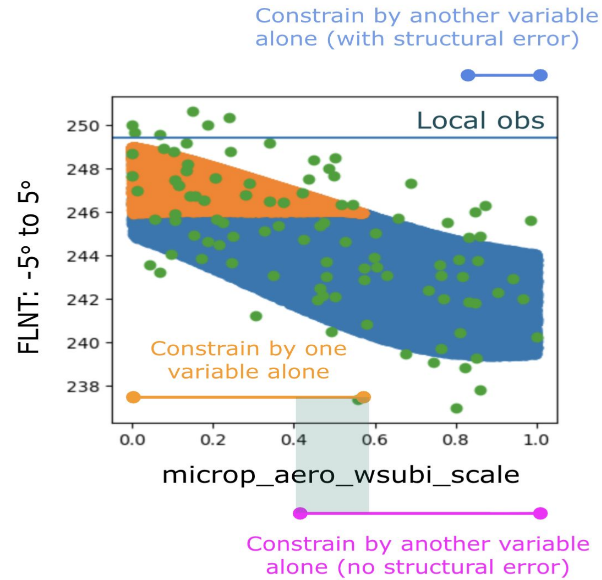
CLM



CAM



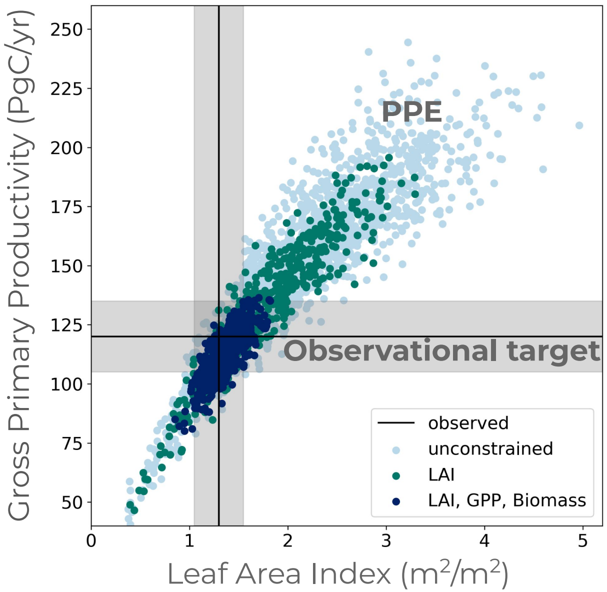
History matching approach
(Yang et al., 2026, JAMES)

Linnia Hawkins, Daniel Kennedy, Katie Dagon, Dave Lawrence

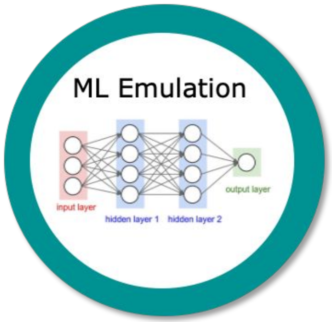
Qingyuan Yang, Greg Elsaesser, Marcus van Lier Walqui, Brian Medeiros, Addisu Semie

Towards a machine learning enhanced version of CESM (CESM3-MLe)

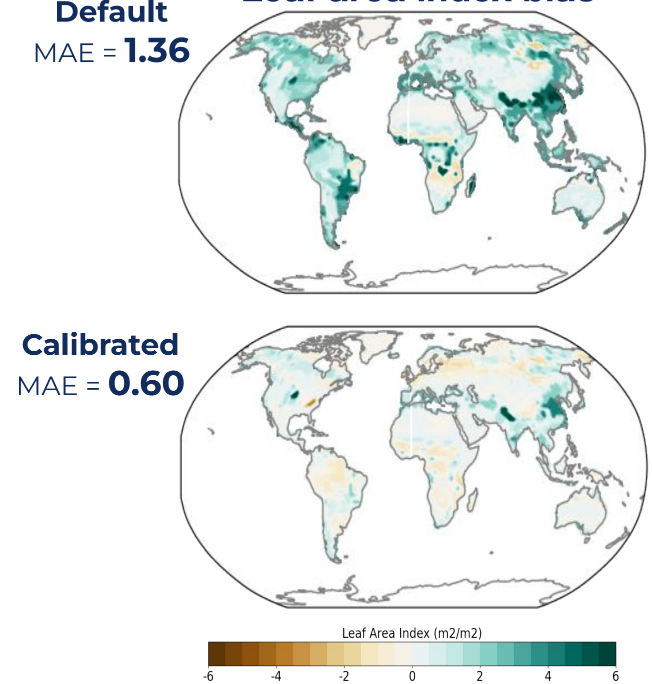
Generate a PPE



Train emulator and calibrate



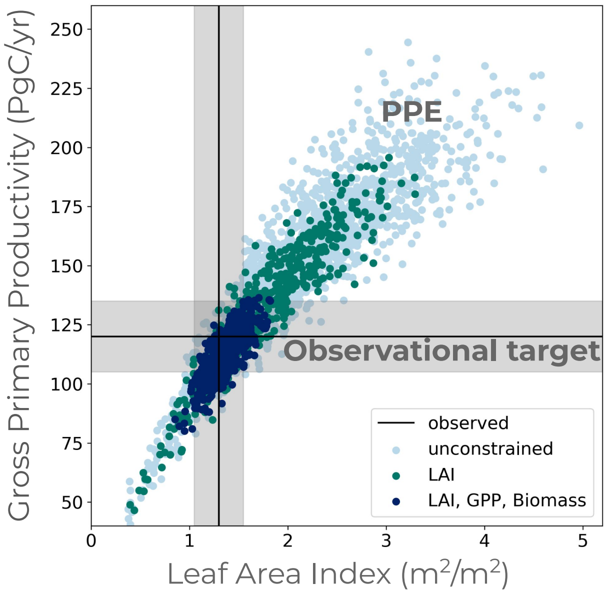
Leaf area index bias



Methods applied to calibrate CLM6 for CESM3

Towards a machine learning enhanced version of CESM (CESM3-MLe)

Generate a PPE



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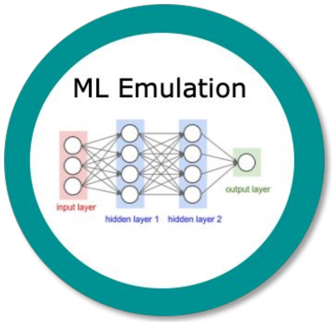
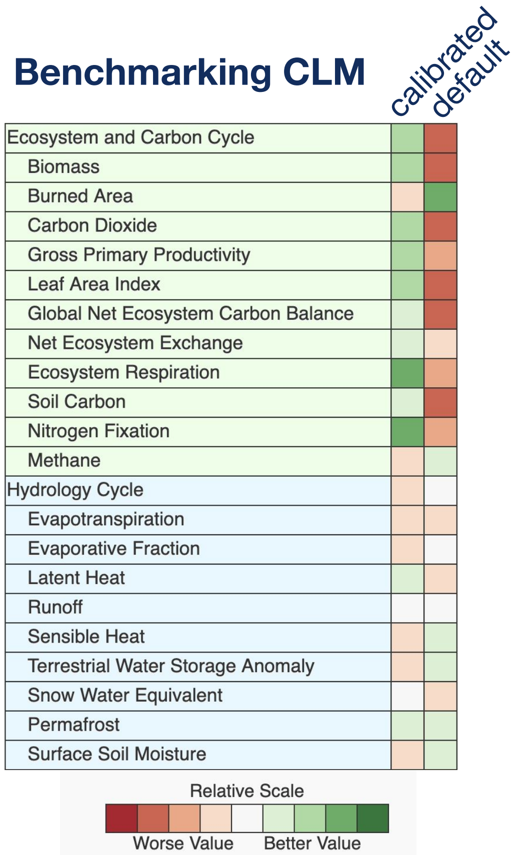


Benchmarking CLM



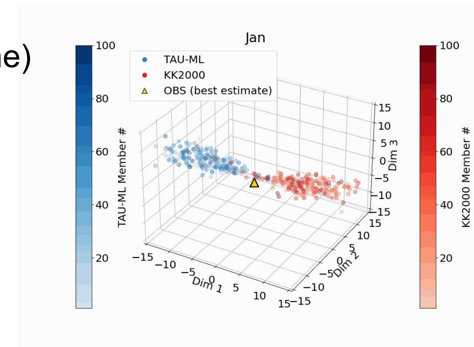
Methods applied to calibrate CLM6 for CESM3

NSF NCAR Operated by UCAR LEAP

From none (other than tuning) to multiple approaches to calibrate CAM!

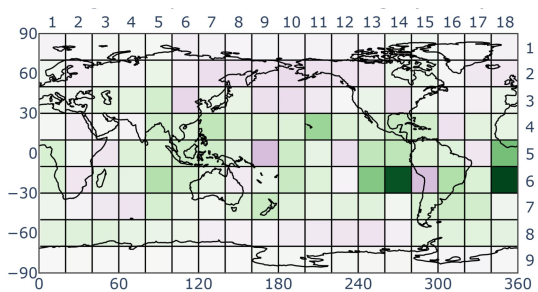
Contrastive learning framework (Da Fan and DJ Gagne)

- Model training and latent feature visualization
- Explainable AI applied to latent distance to identify structural differences
- Bayesian optimization calibration using latent distance



QuadTune (Larson et al., 2025)

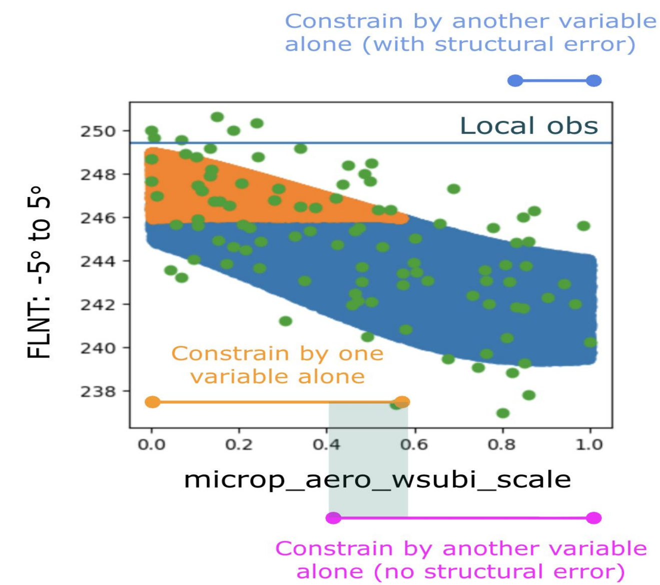
"Poor man's" model tuner. Carves into regions and ~ parameter dependence w/ uncorrelated quadratic emulator



History matching approach

(Yang et al., 2025, JAMES; Yang et al., in prep)

- Simple emulator per target (~2 params as input)
- Target many local climatologies (e.g. Avg. 10° zonal LWCF, SWCF …)
- Detect structural error before parameter estimation, **neglect variables w/ large structural error**



NSF NCAR LEAP

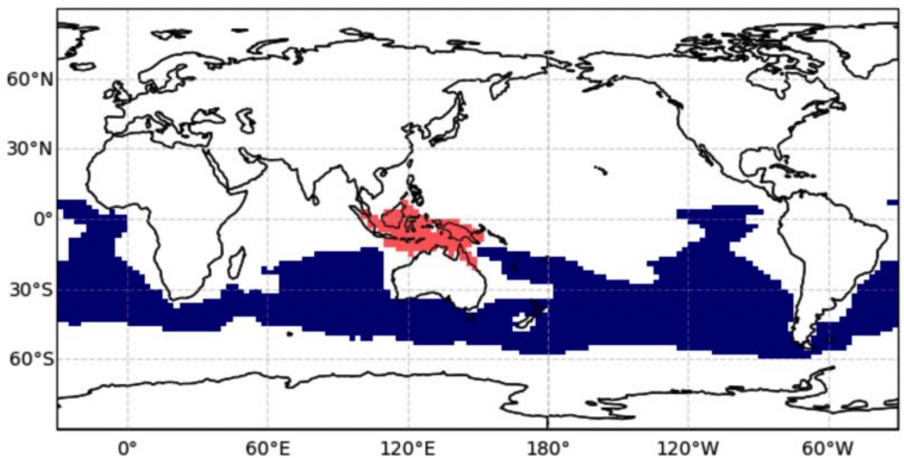
CAM: Additive Gaussian Process Emulator (Yang et al., JAMES, accepted)

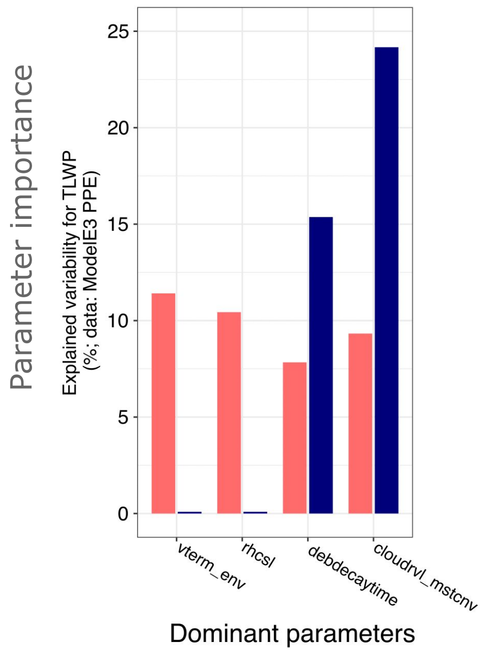
Insight: Individually insensitive parameters can be cumulatively important

Why? Some parameters are only locally/regionally sensitive

Therefore: Emulating only global climatologies may not be sufficient for all problems

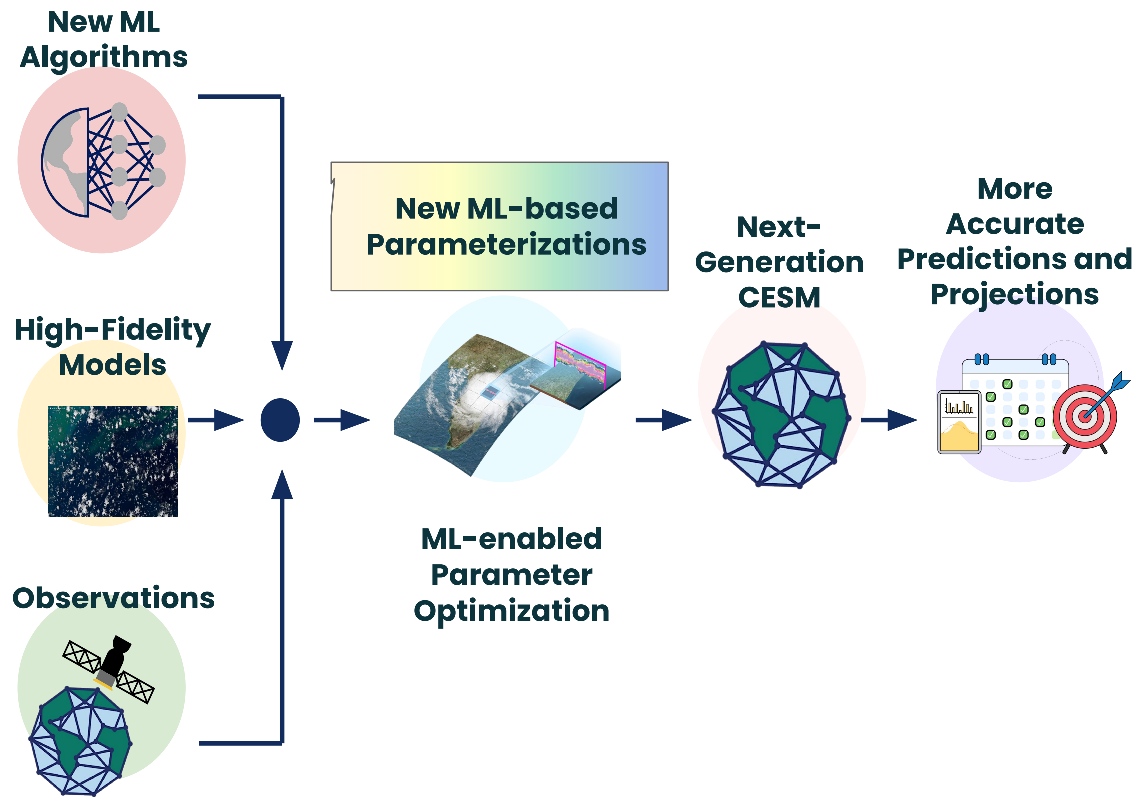
Implication: May be able to both decrease local biases while still calibrating globally





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

M^2LInES Schmidt Sciences

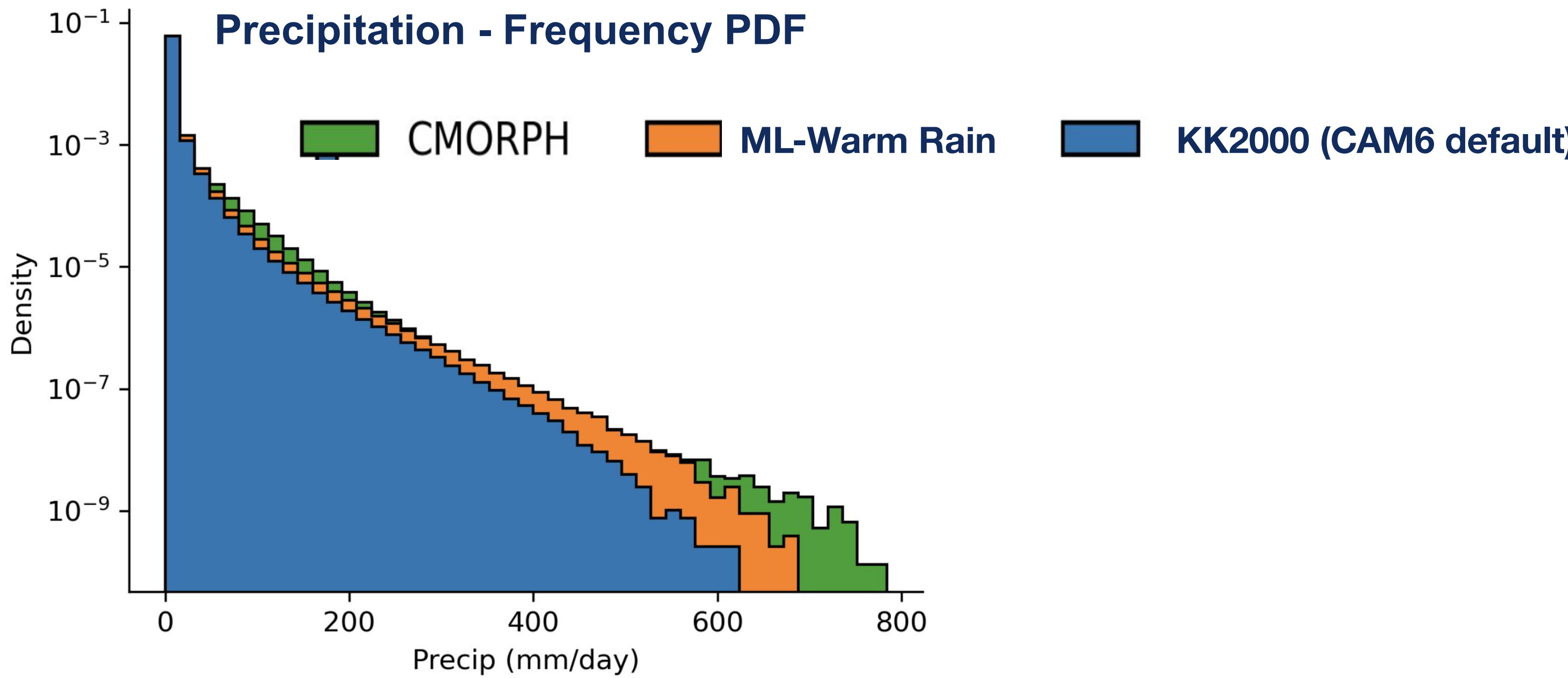
Harness new ML + data to transform CESM

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

Towards a machine learning enhanced version of CESM (CESM3-MLe)

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)



Towards a machine learning enhanced version of CESM (CESM3-MLe)

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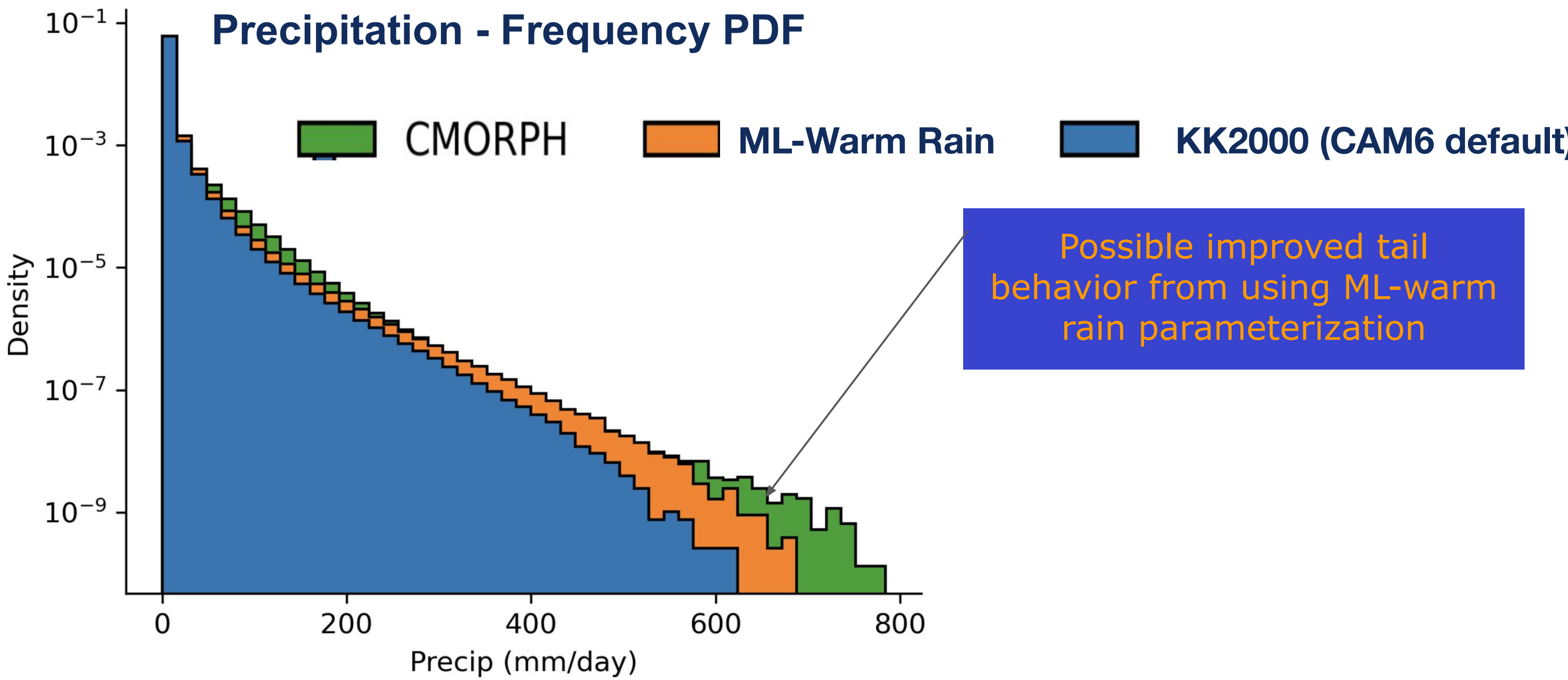
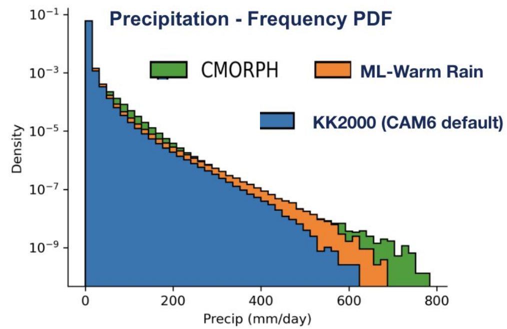
Warm rain microphysics: Emulate cloud droplet autoconversion and accretion with NNs trained on CAM simulations with warm rain process replaced with highly resolved bin microphysics (TAU code)



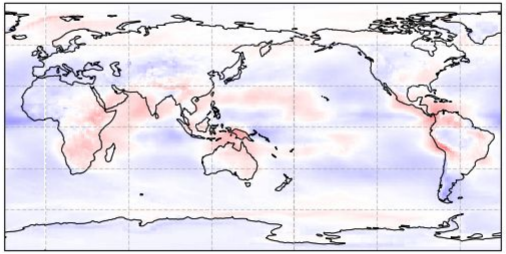
Developing workflow to recalibrate after ML parameterization implemented

1. ML warm rain microphysics → improvement in rainfall precip - frequency PDF

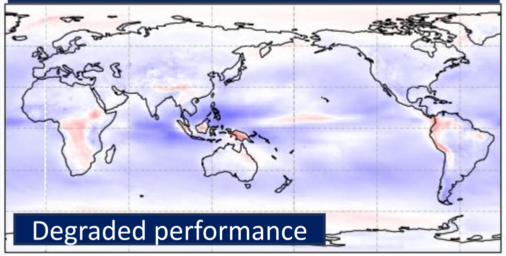


2. But, likely will see degraded performance for other fields with new ML parameterization

CAM default - observation

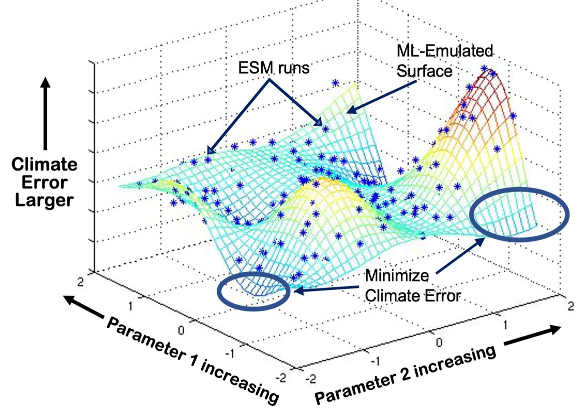


CAM with warm rain ML- observation



Schematic only; representative of a climatological radiation or cloud field

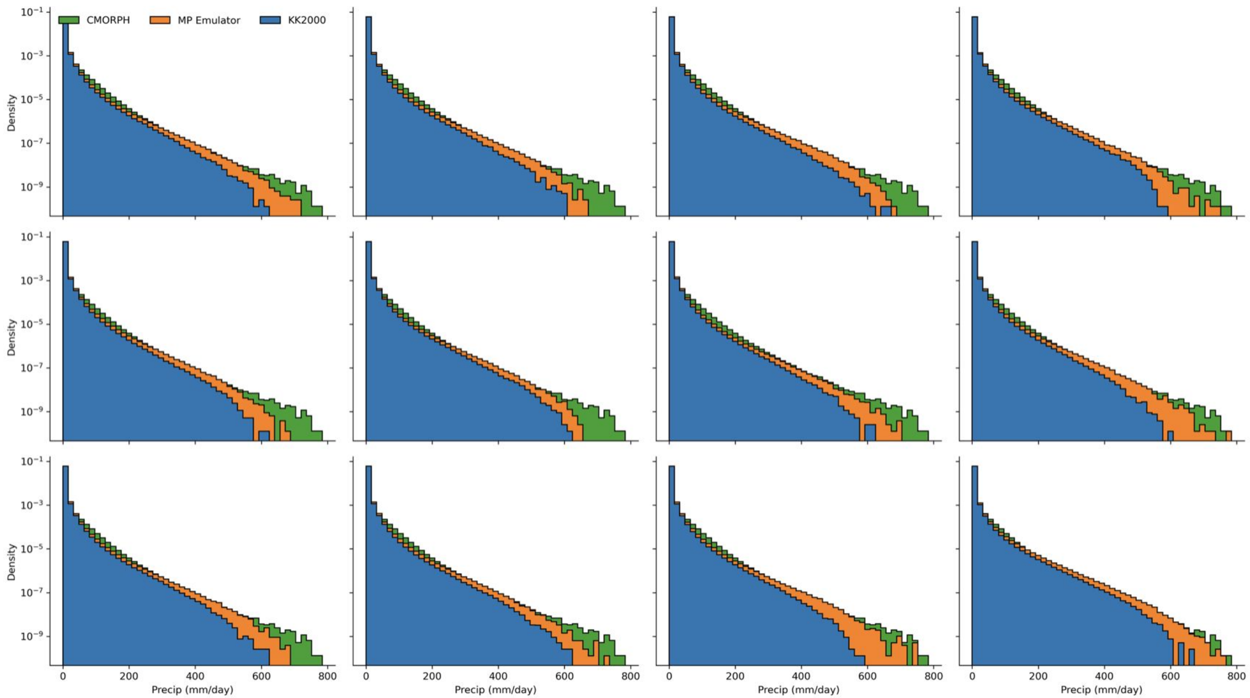
3. Using ML for auto-tuning, re-calibrate CAM to correct the degraded performance, while (hopefully) simultaneously retaining the improvement in rainfall intensity - frequency distribution



Developing workflow to recalibrate after ML parameterization implemented

Precipitation - Frequency PDF

CMORPH   ML-Warm Rain   KK2000 (CAM6 default)

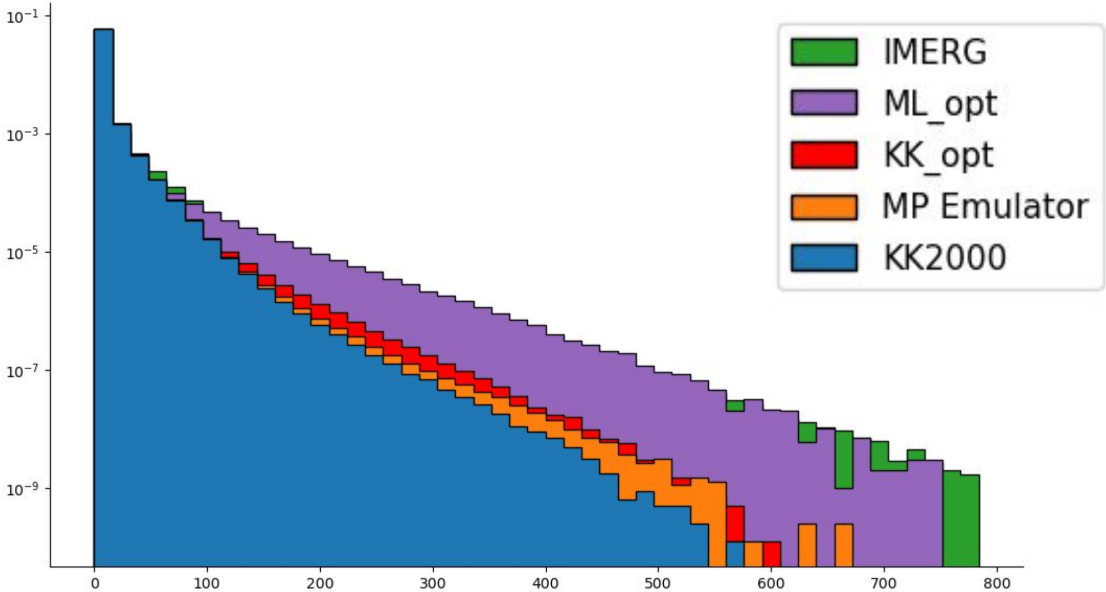


Each plot is for randomly pulled parameter set from a 200 member PPE with and without ML warm rain parameterization

→ Improvement from ML warm rain microphysics parameterization is likely to be retained after recalibration

Calibration

Precipitation - Frequency PDF



ML warm rain configuration can be calibrated to achieve good PDF

Original KK2000 parameterization cannot

* Note that there may be some degradations in climatological fields in these calibrations

Figure from Addisu Semie

Accelerating progress towards evaluation of the hypothesis that ML can help build improved ESMs

This material is based upon work supported by the National Center for Atmospheric Research, which is a major facility sponsored by the National Science Foundation under Cooperative Agreement No. 1852977.

CESM-MLe Integration Team

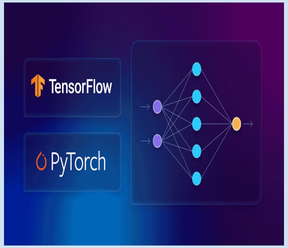
Enables productive and sustained interactions between LEAP, M^2LInES, and other projects and CESM scientists and developers

Integration team

FTorch Bridge

Python

Machine learning research and development are predominantly conducted in Python.



FTorch

Provides bridge to connect ML models and Earth System Models

Fortran

Many large-scale scientific models are developed using Fortran, C, or C++.

FTorch Deep Convection (YOG) Integration

```
FTorch_CAM_integration/
├── src/
│   └── cam/                                    #
│       ├── Phys_control.F90
│       ├── physpkg.F90
│       ├── yog_intr.F90
│       ├── nn_interface_CAM.F90
│       ├── nn_convection_flux.F90
│       └── nn_cf_net.F90
│
├── libraries/
│   └── FTorch/
│       └── FTorch_cesm_interface.F90
│
├── docs/
│   ├── build_instructions.md
│   └── troubleshooting.md
│
├── examples/
│   └── user_nl_cam
│
├── MODEL_CARD.md
└── README.md
```

Documentation & tools

leap-stc/integration_team

Documentation

FTorch Deep Convection (YOG) Integration

This repository documents and provides sources for integrating a PyTorch-based deep-convection scheme (YOG) into CESM/CAM using **FTorch**.

- **Component:** CAM (CESM3)
- **What's replaced:** ZM/YOG convection tendencies via FTorch TorchScript model
- **Key idea:** Keep CAM physics + vertical remapping intact; swap the NN call with a TorchScript forward pass (FTorch), preserving CAM data flow.

Repository Structure

```
FTorch_CAM_integration/
├── src/
│   └── cam/                    # Modified CAM physics source files
│       ├── Phys_control.F90
│       ├── physpkg.F90
│       ├── yog_intr.F90
│       ├── nn_interface_CAM.F90
│       ├── nn_convection_flux.F90
│       └── nn_cf_net.F90
│
├── libraries/
│   └── FTorch/
│       └── FTorch_cesm_interface.F90    # Wrapper for FTorch model calls
│
├── docs/
│   ├── build_instructions.md
│   └── troubleshooting.md
│
├── examples/
│   └── user_nl_cam
│
├── MODEL_CARD.md
└── README.md
```

Tools & support

Functional Unit Test set up

This example sets up a functional test on Derecho. The functional test is just a place to test your ml model using FTorch in Fortran. Please file an issue if you run into problems.

Developed by Adrianna Foster & Linnia Hawkins

1) Clone CTSM

`git clone https://github.com/ESCOMP/CTSM.git CTSM`

I suggest cloning to your work directory $WORK or /glade/work/username/

2) Add in some mods

```
cd CTSM
git remote add jedwards https://github.com/jedwards4b/ctsm.git
git fetch jedwards
git checkout ftorch_d1fccec99
./bin/git-fleximod update
cd src/fates
git remote add linnia https://github.com/linniahawkins/fates
git fetch linnia
git checkout ml_example
```

3) Set up your environment

```
export Torch_DIR=/glade/work/jedwards/conda-envs/ml5.6/
module load conda
conda activate ctsm_pylib # or some python environment with matplotlib and numpy
```

#cesm-integration

Parameterizations in development for possible inclusion in CESM3-MLe

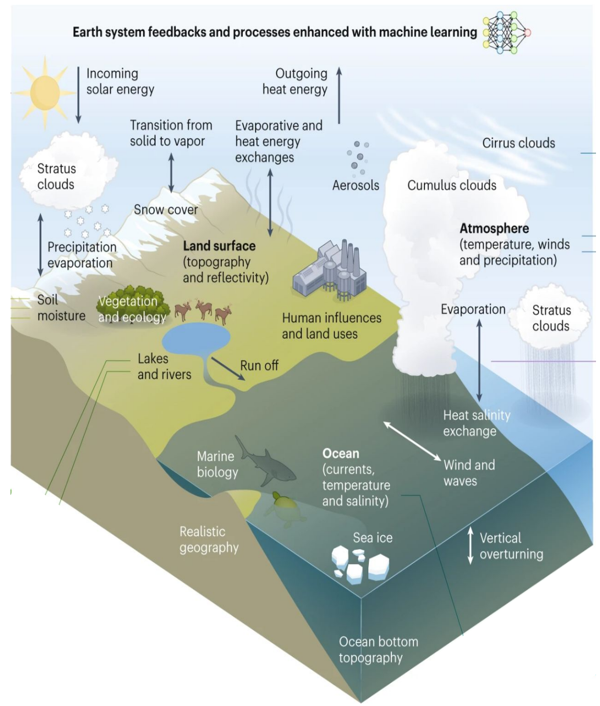
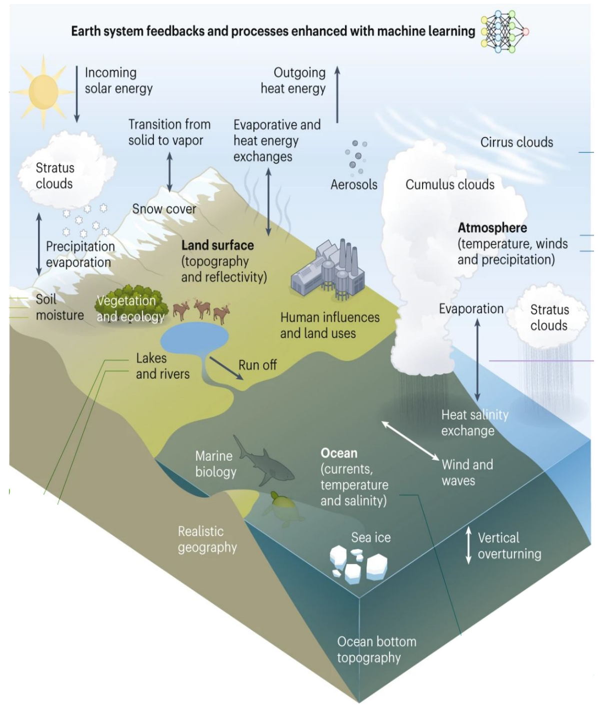


Figure modified from Eyring, Gentine, Camps-Valls, Lawrence, Reichstein (Nature Climate Change, 2024)

Parameterizations in development for possible inclusion in CESM3-MLe



Phenology

Pedotransfer functions

Sea ice heat conduction

Ice sheet friction

Sea ice floe perimeter

Warm rain microphysics

Ice microphysics

Convection

Convective triggering

Cloud cover

Vertical Mixing (KPP)

Ocean Mesoscales

Air-sea turbulent fluxes

ML-based calibration of CAM, CLM, MOM6 independently

LEAP

M²LInES

ICON, E3SM, lit.

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

Parameterizations in development for possible inclusion in CESM3-MLe

Radiation

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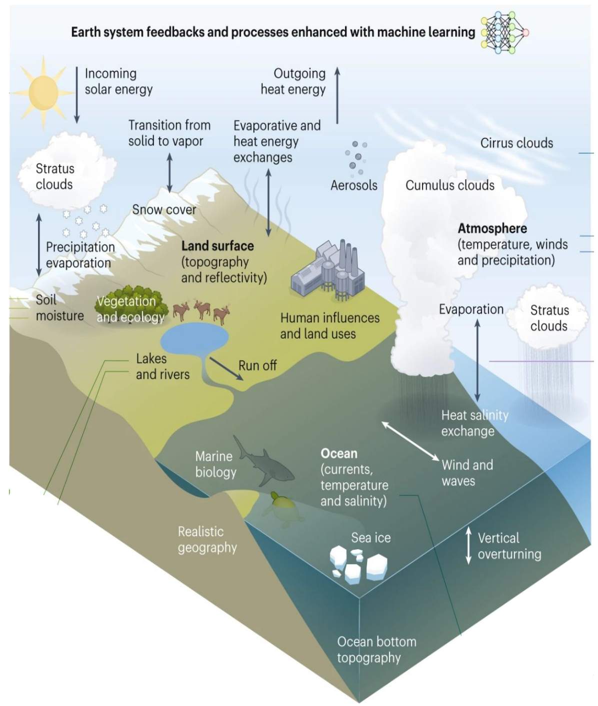

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Initial CESM3-MLe AMIP configuration (by CMIP meeting in March?)

Radiation

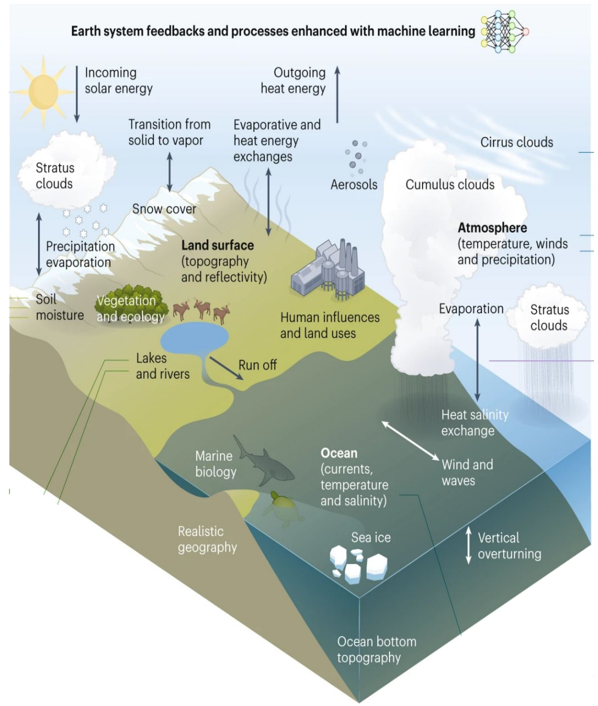
Phenology

Pedotransfer functions

Sea ice heat conduction

Ice sheet friction

Sea ice floe perimeter



Gravity Waves

Warm rain microphysics

Ice microphysics

Convection

Xavier Levine 12:10 Wed

Convective triggering

Cloud cover

Vertical Mixing (KPP)

Ocean Mesoscales

Air-sea turbulent fluxes

LEAP

M²LInES

Other

Diajeng Atmojo 9:00 Thurs, PCWG

ML-based **calibration of CAM, CLM,** MOM6 independently

Qingyuan Yang

Linnia Hawkins, LMWG

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

LEAP

M^2LInES Schmidt Sciences

(After CESM3 push) Move forward 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, regular development meetings)
- Hybrid Model Implementation Workshop (joint with ICON-ML) June 5-9

Anticipate that there will be challenges

- Reliability in out-of-training climates
- Potential for CESM model instabilities
- Unanticipated interdependencies
- Substantially new simulated climate may degrade orthogonal simulation aspects
- New tuning challenges with some knobs removed

Defining Success for CESM3-MLe

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

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

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Fundamental Challenge is that it is HARD to build a new coupled model!

- Schmidt Sciences call on coupled model calibration
- Use CESM3-MLe as 'case study' to see if we can develop methodologies to produce a coupled model faster
- Ideas: Utilize initialized prediction, efficient component calibration, hierarchical calibration stepping up through timescales, faster spinup methods, …

Extra Slides

Emulators: CREDIT - Community Research Earth Digital Intelligence Twin

What is CREDIT?

An ***open foundational platform*** for developing and deploying AI weather and Earth system prediction models for autoregressive systems.

CREDIT enables users to build custom data and modeling pipelines to load data, train configurable AI forward models, and deploy them for real-time forecasting, hindcasting, or scenario projections.

CREDIT offers both scientifically validated model configurations and endless customization for any use case.

Datasets

ERA5 | CAM | GFS | CONUS 404

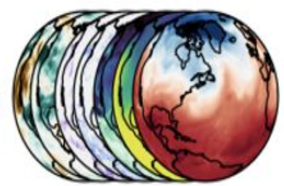
Models

WXFormer | NCAR FuXi | Graph Recurrent Transformer

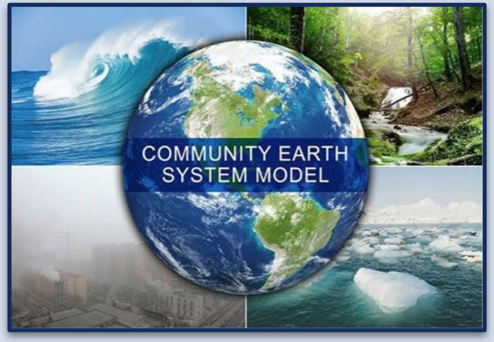
Physics

Mass Conservation | Energy Conservation | Moisture Budget

Outputs



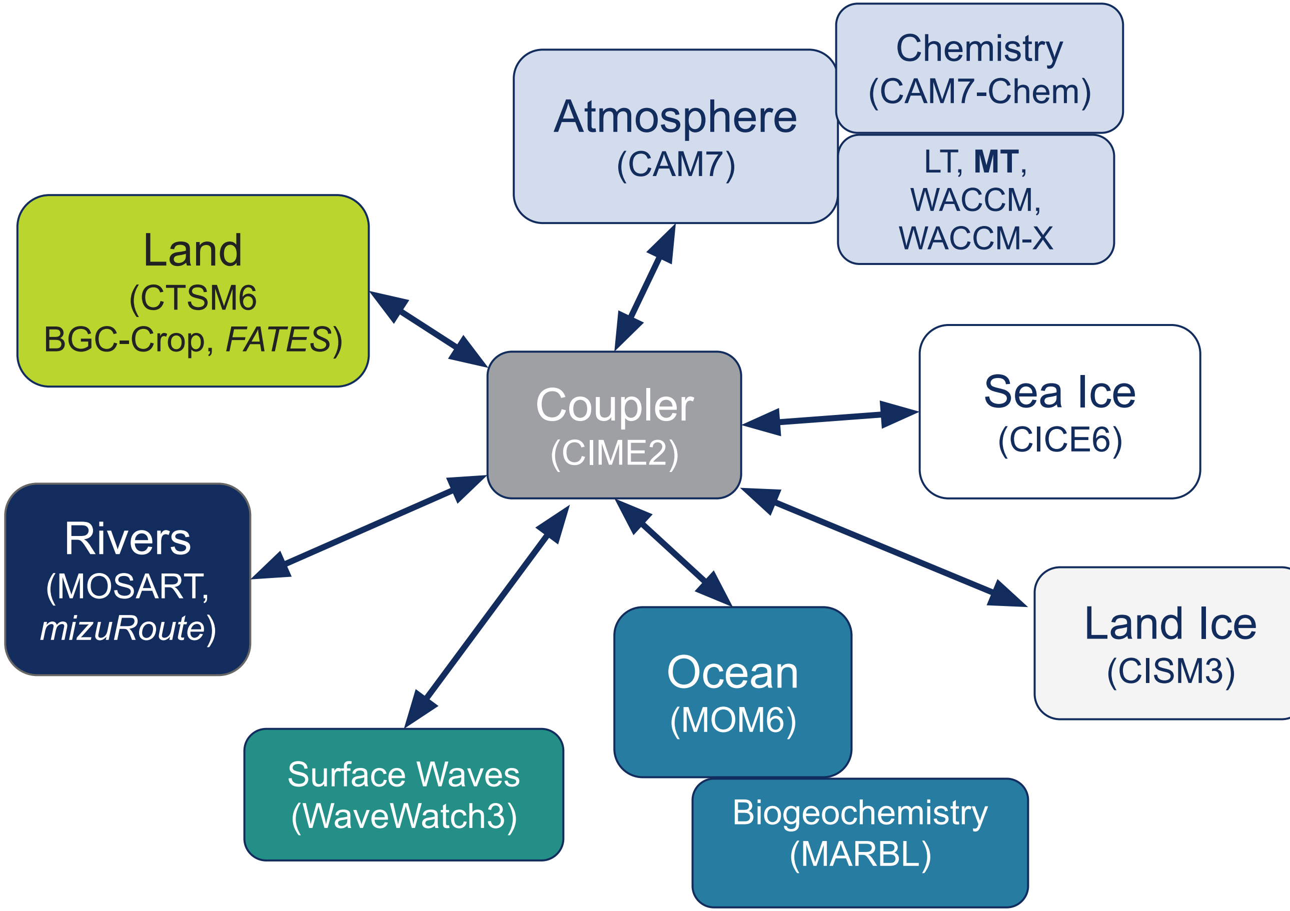
Working towards CESM3



Significant updates to all component models

Targeting use of CESM3 for CMIP7

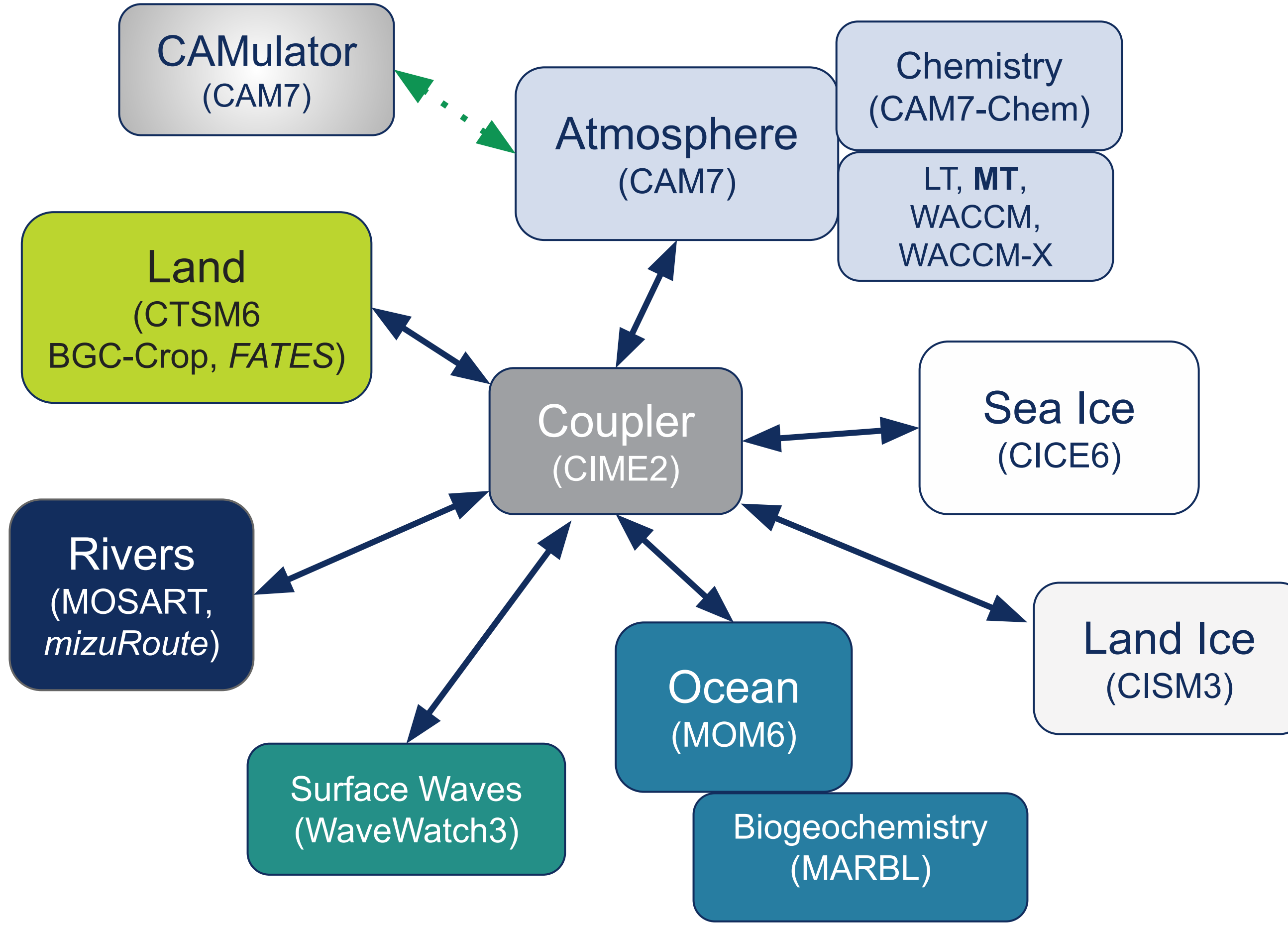
Emissions-driven configuration to be default, with interactive ice sheets and fire aerosol emissions?



CAMulator as part of CESM3 release

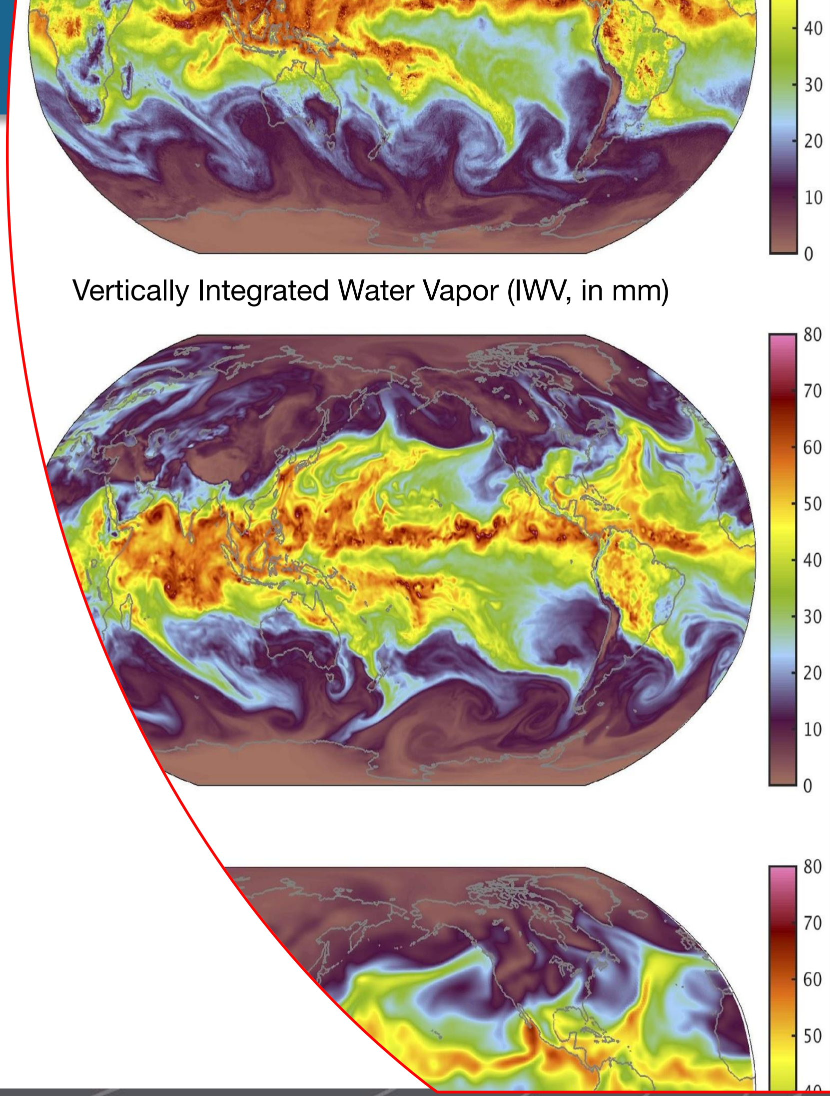
Supported CAMulator, trained on CAM7

Flexible enough to easily train on new simulations or for different priority emulated targets



Towards emulation of CESM High Resolution simulations?

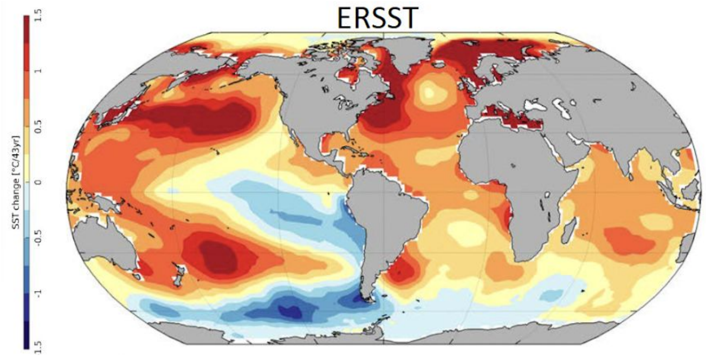
- **CESM1.3(HR): 0.25° atm/lnd, 0.1° ocn**
  - 10-member ensemble of historical and several projections

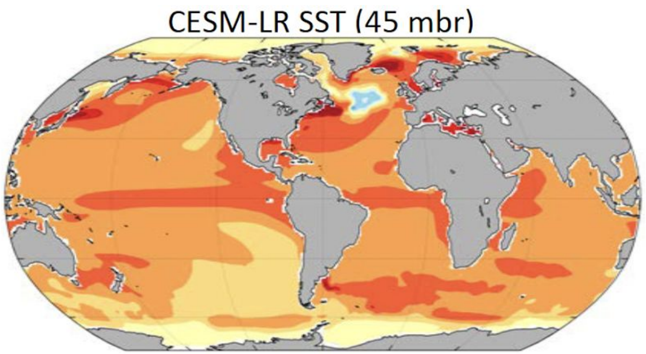


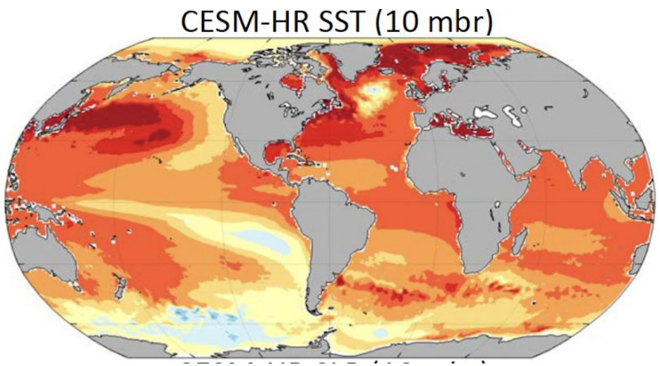
Vertically Integrated Water Vapor (IWV, in mm)

Chang et al. (2020, JAMES)

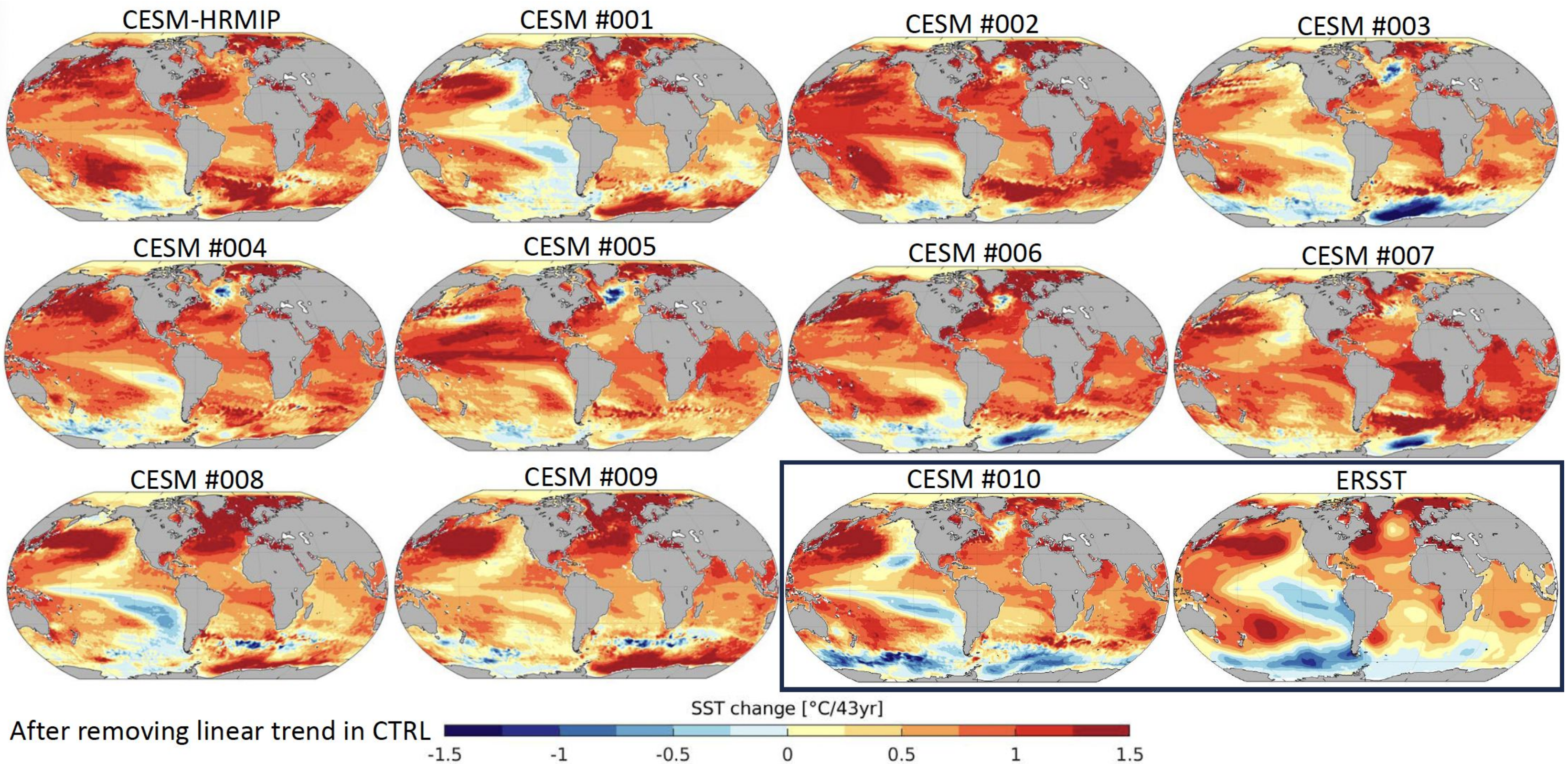
Linear trend (1980-2022) in SST







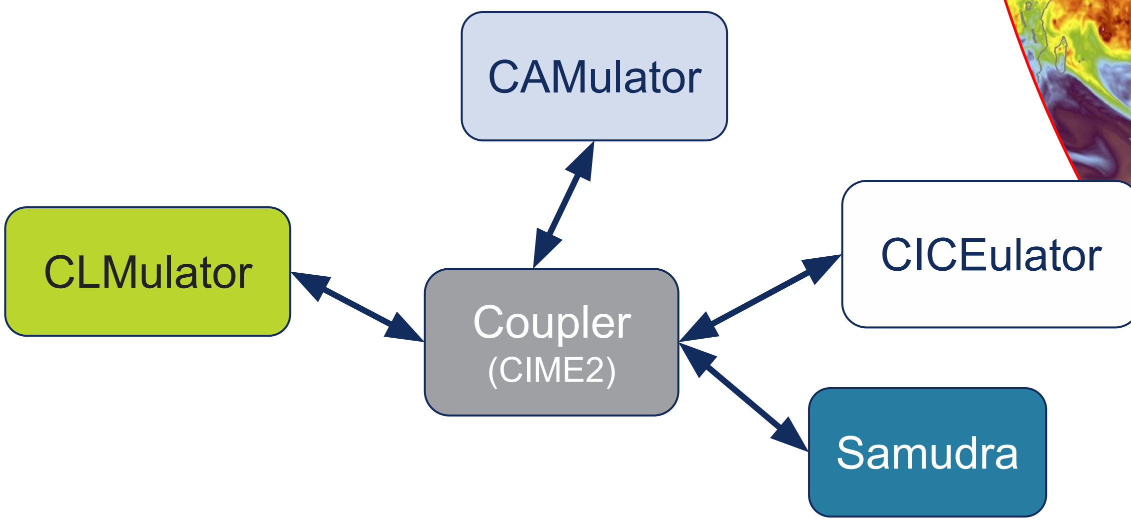
Linear trend (1980-2022) in SST

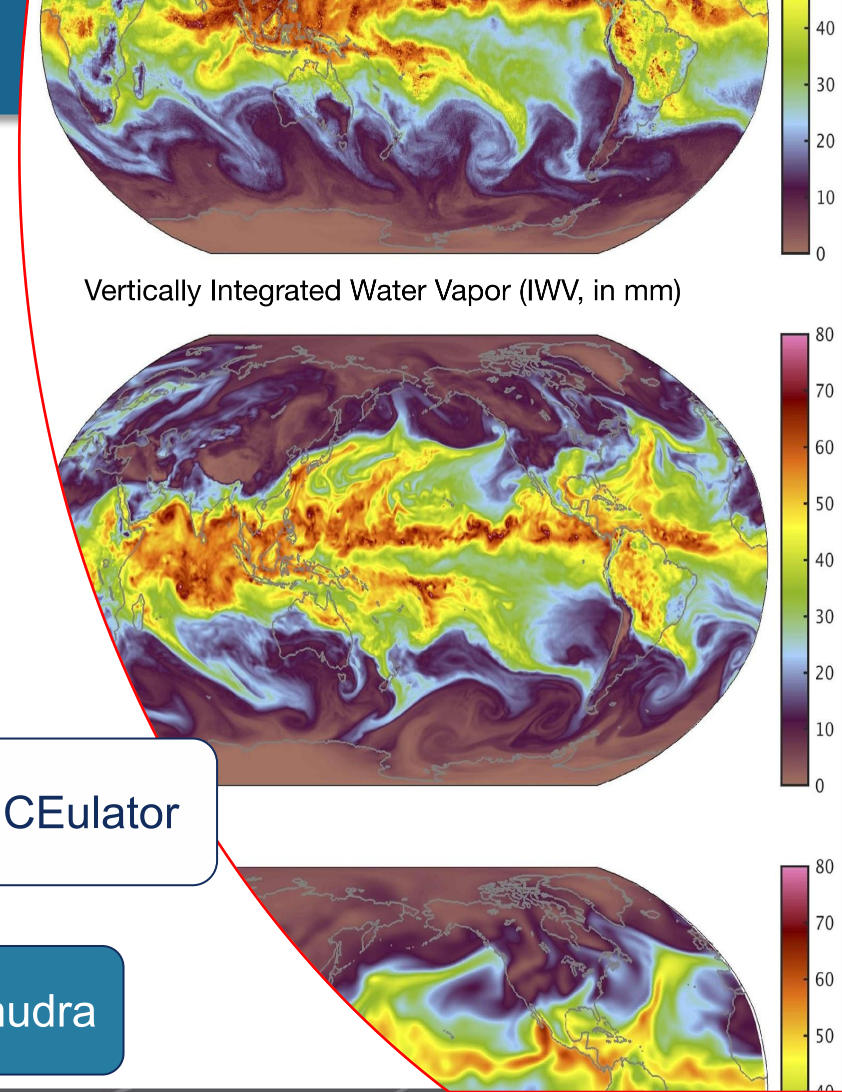


After removing linear trend in CTRL

CESM resolution hierarchy: progress and plans

- CESM1.3(HR): 0.25° atm/lnd, 0.1° ocn
- Developing CESM3(HR) version
  - But, ~500K pe-hrs/syr
  - 100M pe-hrs for 200 yrs simulation (!)
  - Utilize a CESMulator to build ensembles of single or a small number of realizations of CESM3(HR)?





Chang et al. (2020, JAMES)

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

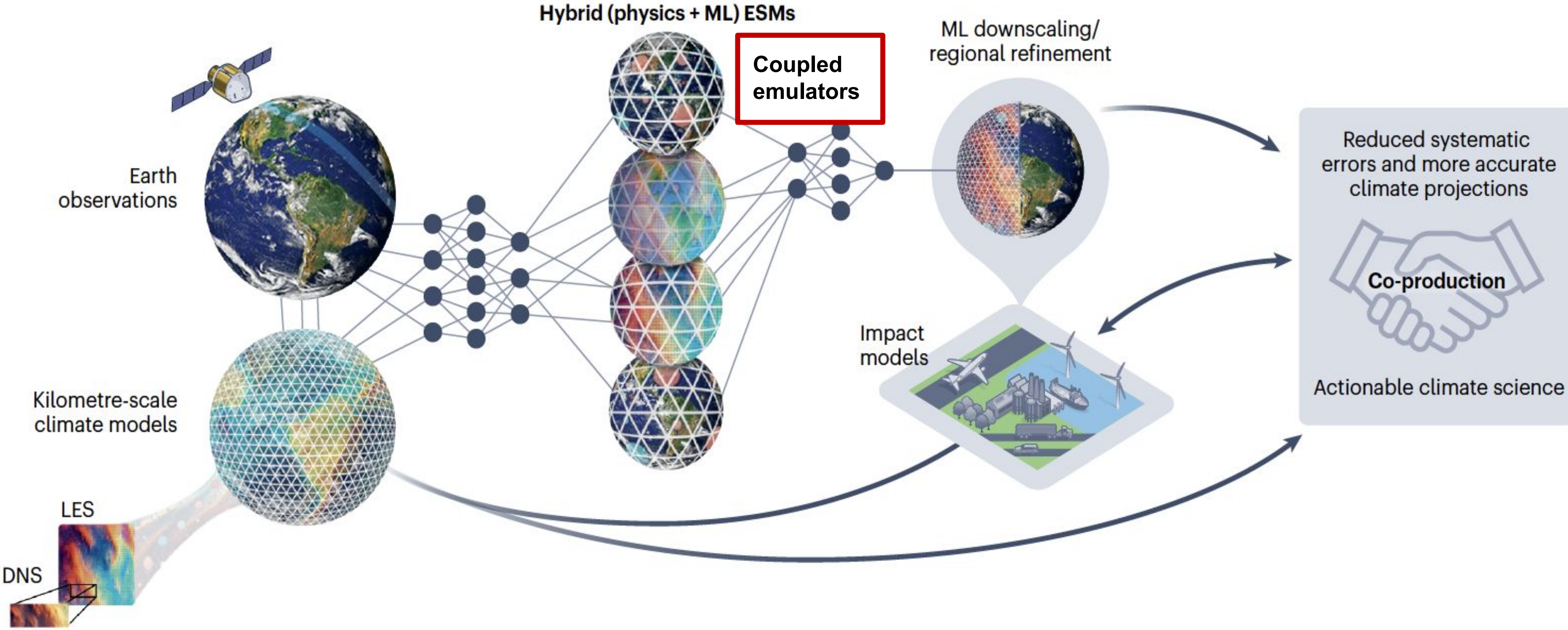
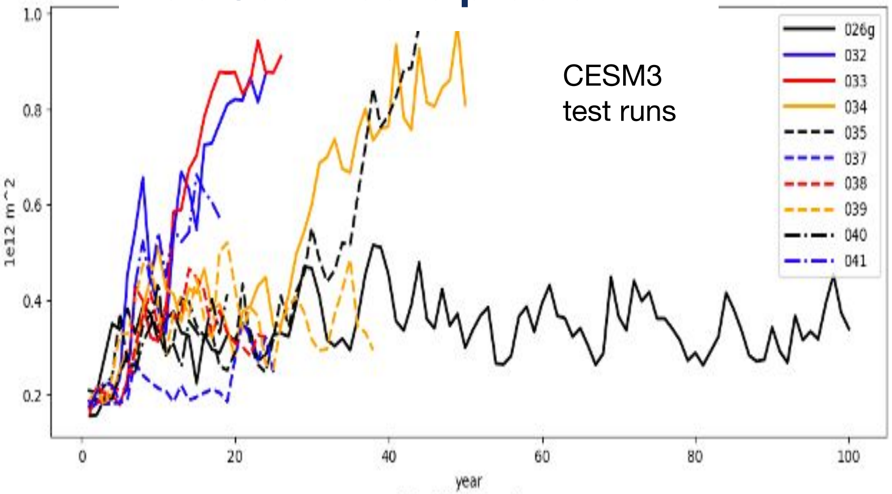


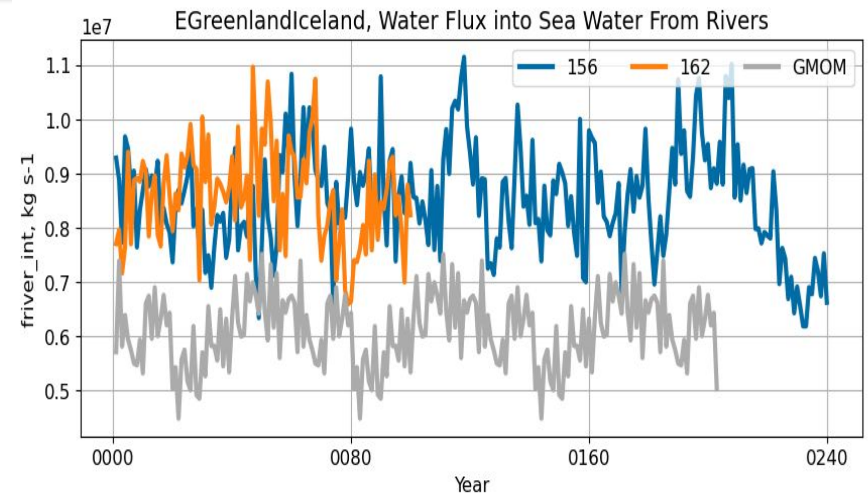
Figure from Eyring, Gentine, Camps-Valls, Lawrence, Reichstein (Nature Climate Change, 2024)

Can AI help accelerate process of building a coupled model?

Building coupled models is hard

Lab Sea Freeze problem





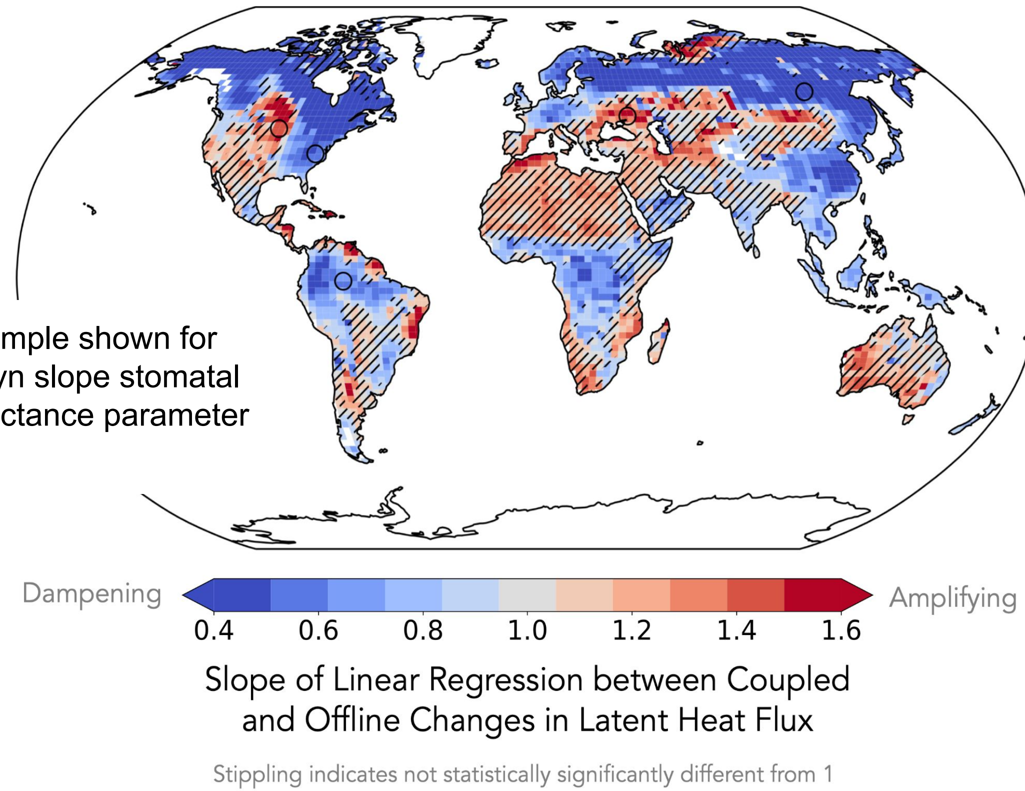
- CGD-ML group is looking at Lab Sea freeze issue (excessive freshwater, but from where?)
- Can AI identify signatures/precursors to Lab Sea freeze that can help point developers to processes to target for improvement?
- Take advantage of the 50+ member database of runs that freeze and a new pertlim ensemble that we are generating

LEAP v2.0: Accelerate the hybridization and joint optimization

Success of LEAP: Land Model parameter calibration

Challenge for LEAP2.0: Translating work to the coupled climate model: Impact of parameter perturbations can be different in Coupled vs Land-only (offline) simulations, even exhibiting a different sign of response

Atmospheric modulation of parameter impacts on latent heat flux



Example shown for Medlyn slope stomatal conductance parameter

Figure from Zarakas et al., in review

Thank you!