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

David Lawrence
CESM Chief Scientist

NSF | NCAR

LEAP

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

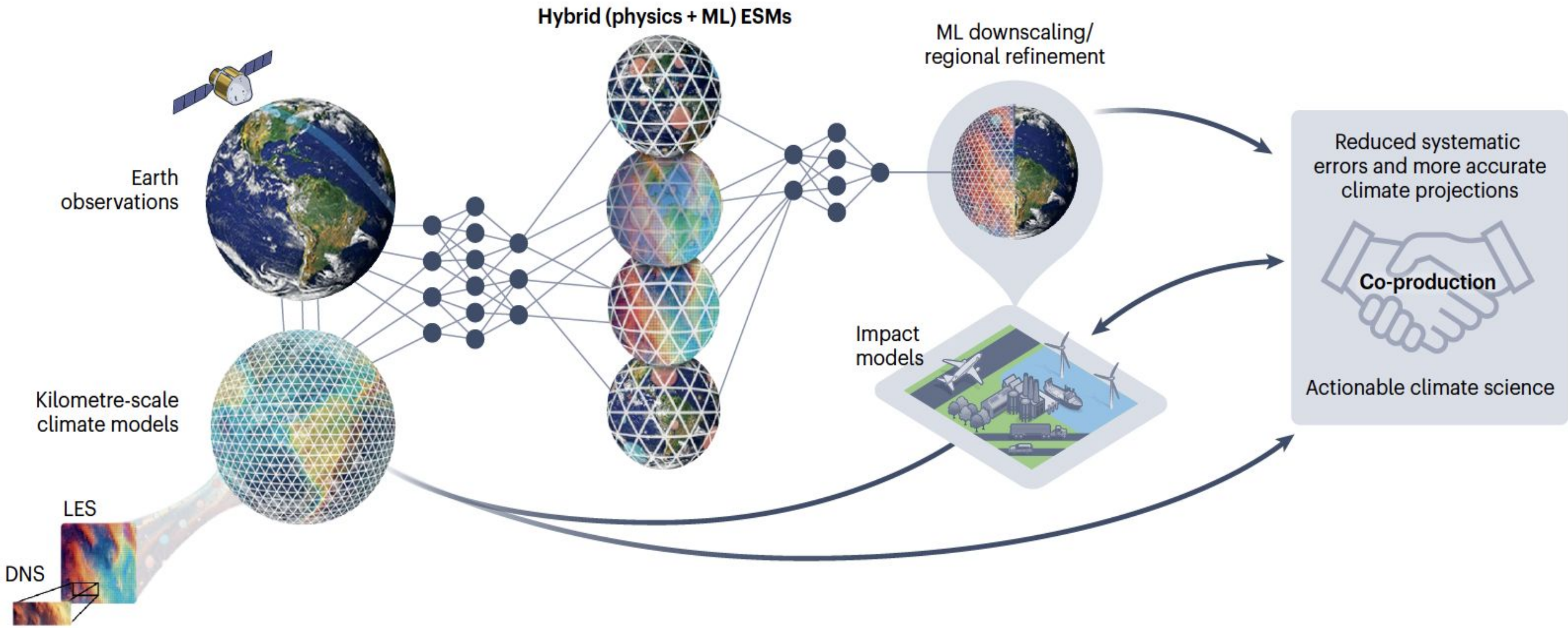
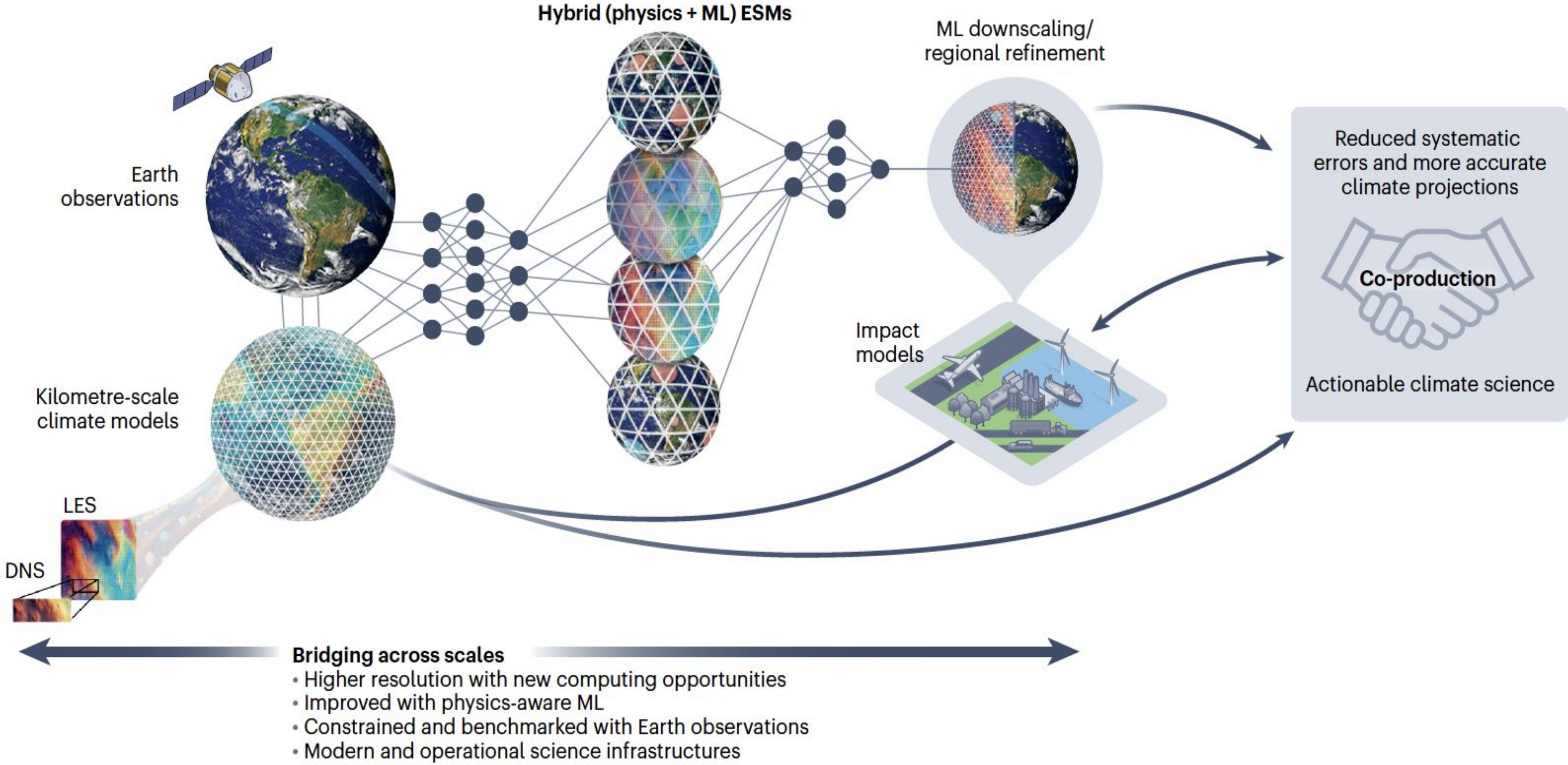


Figure from Eyring, Gentine, Camps-Valls, Lawrence, Reichstein (Nature Climate Change, 2024)

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



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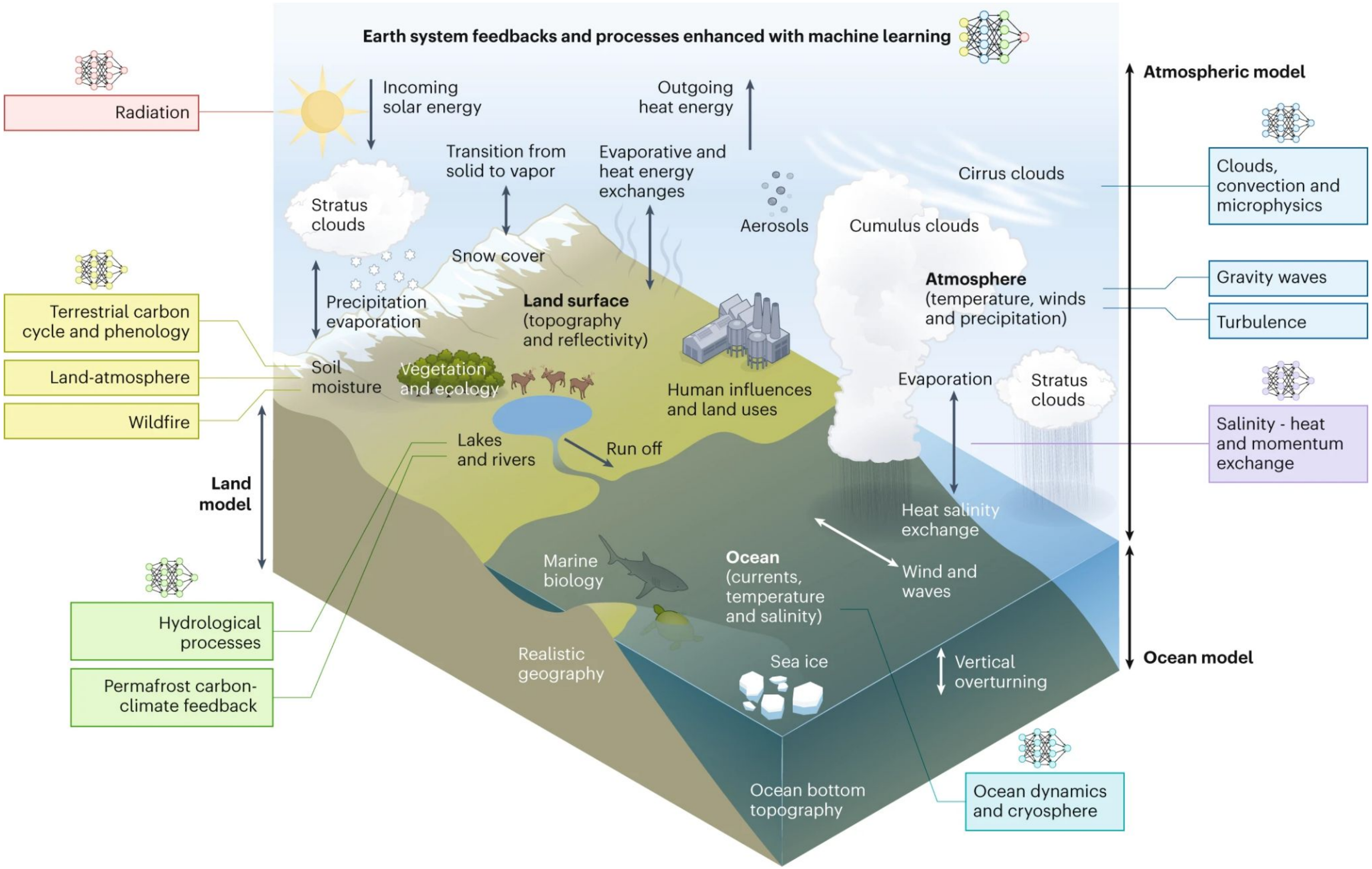
Next-generation Earth System modeling to address urgent mitigation and adaptation needs



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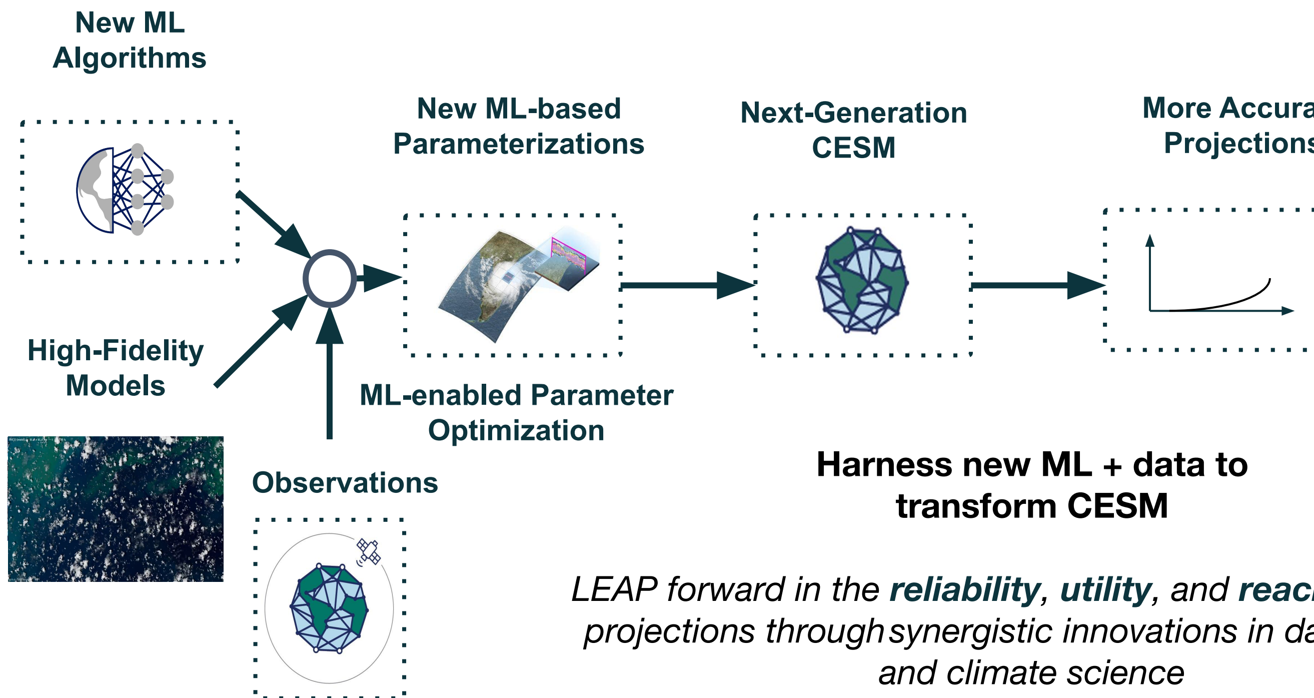
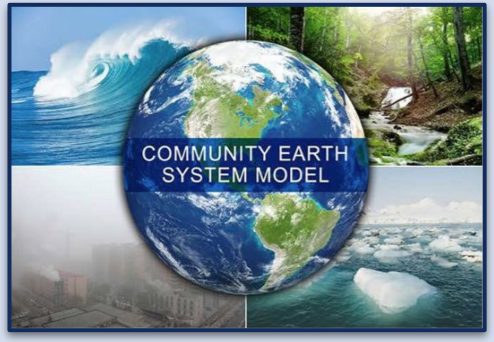


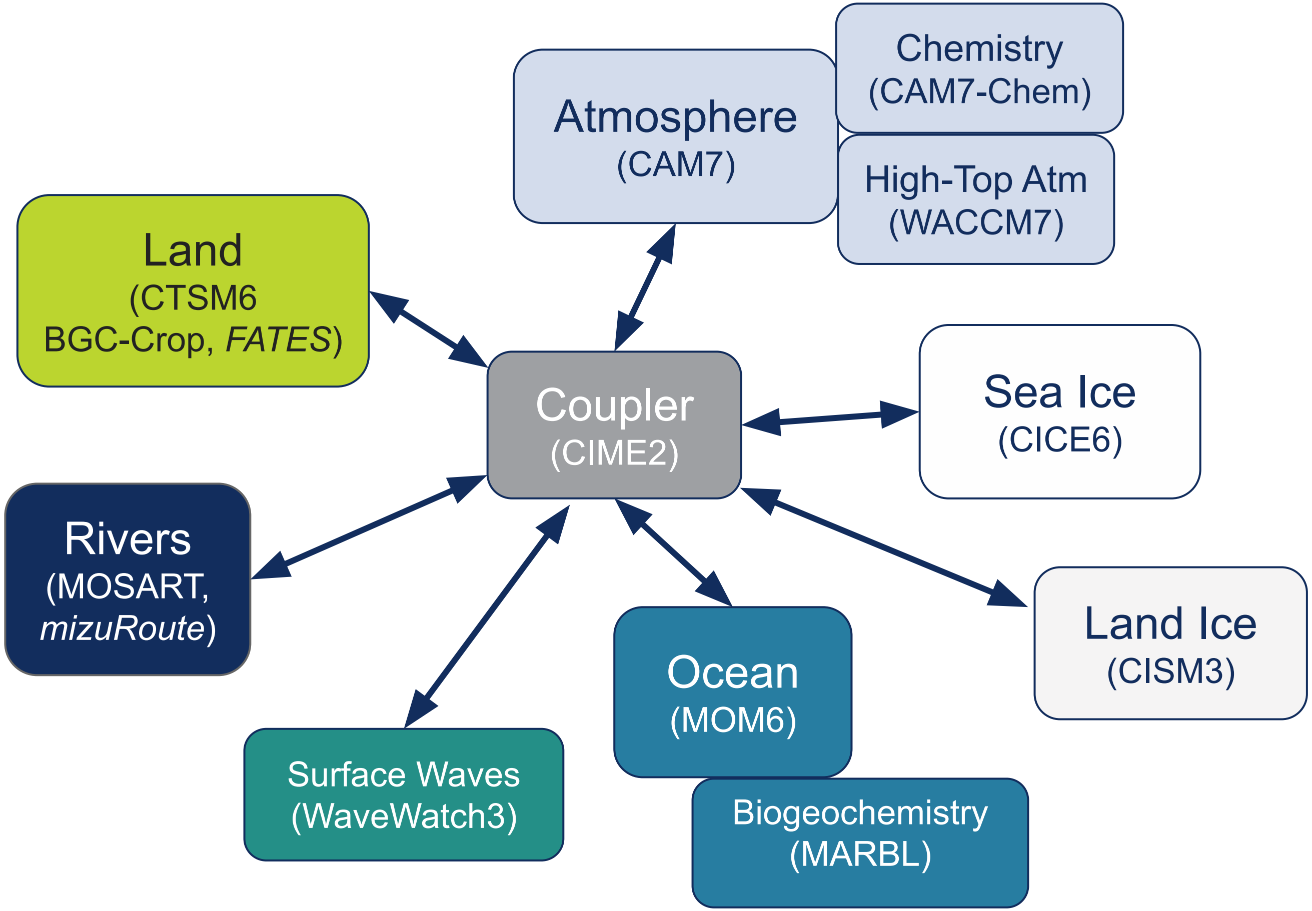
Harness new ML + data to transform CESM

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

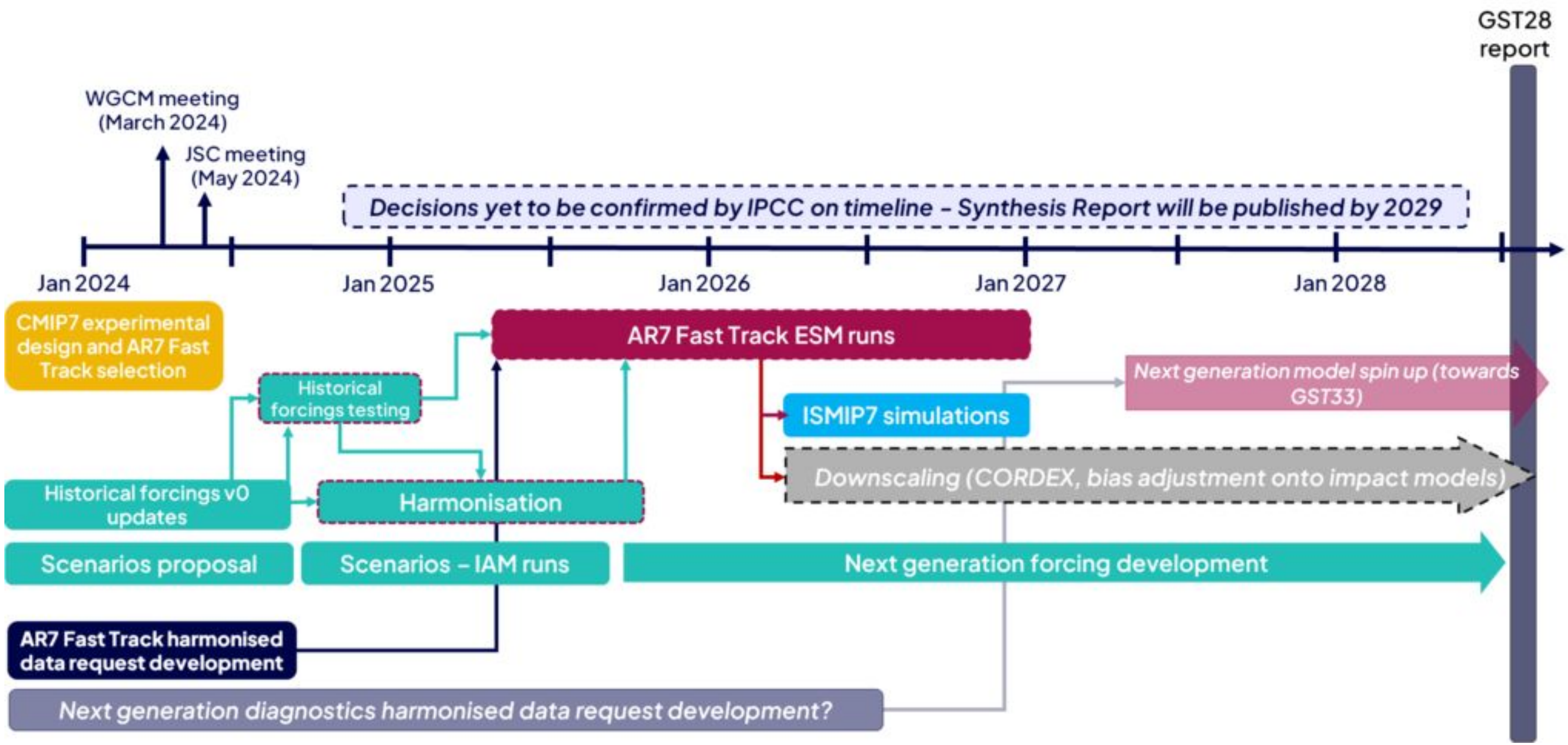
Working towards CESM3



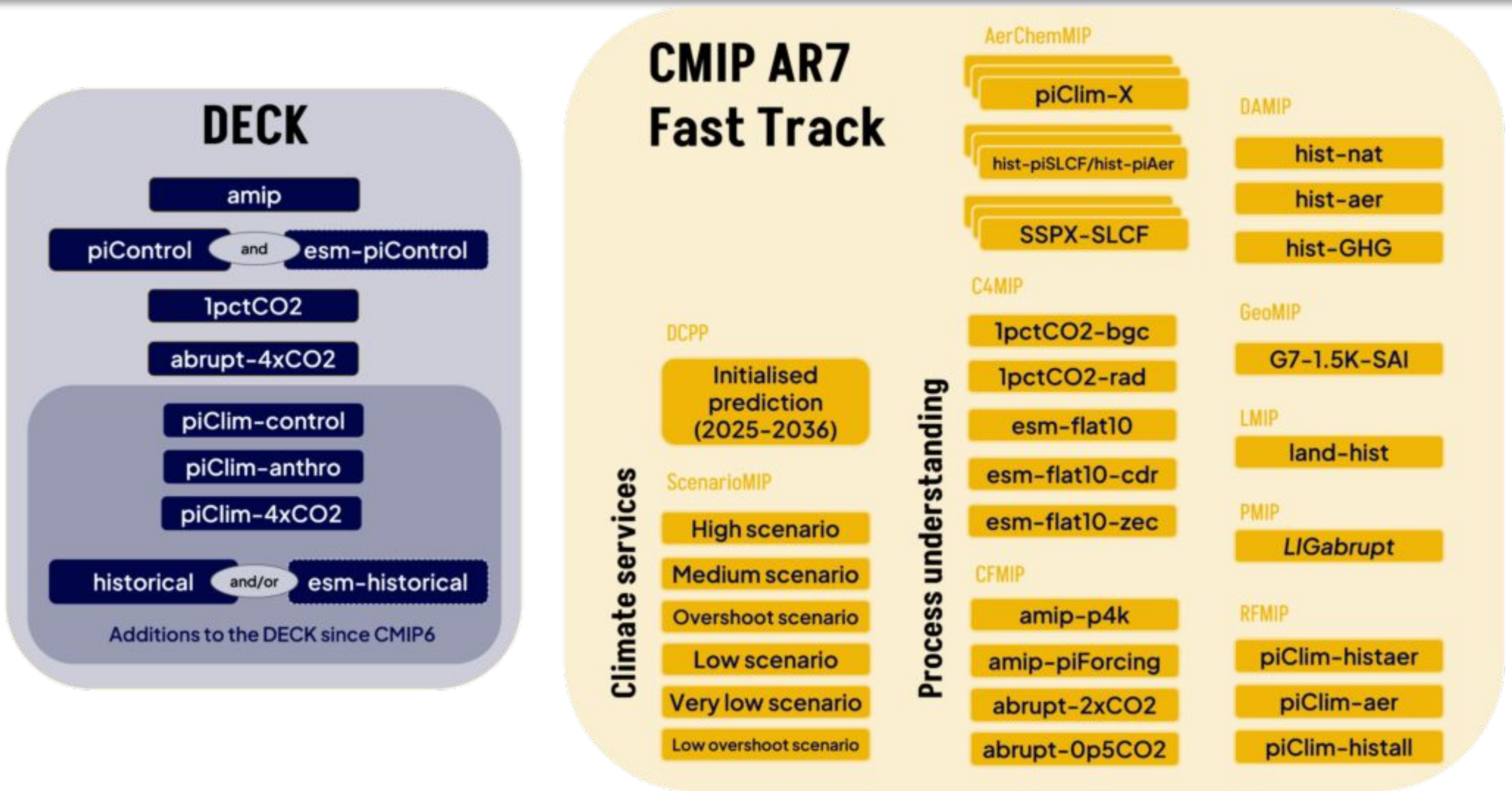
Significant updates to all component models



CMIP Timelines



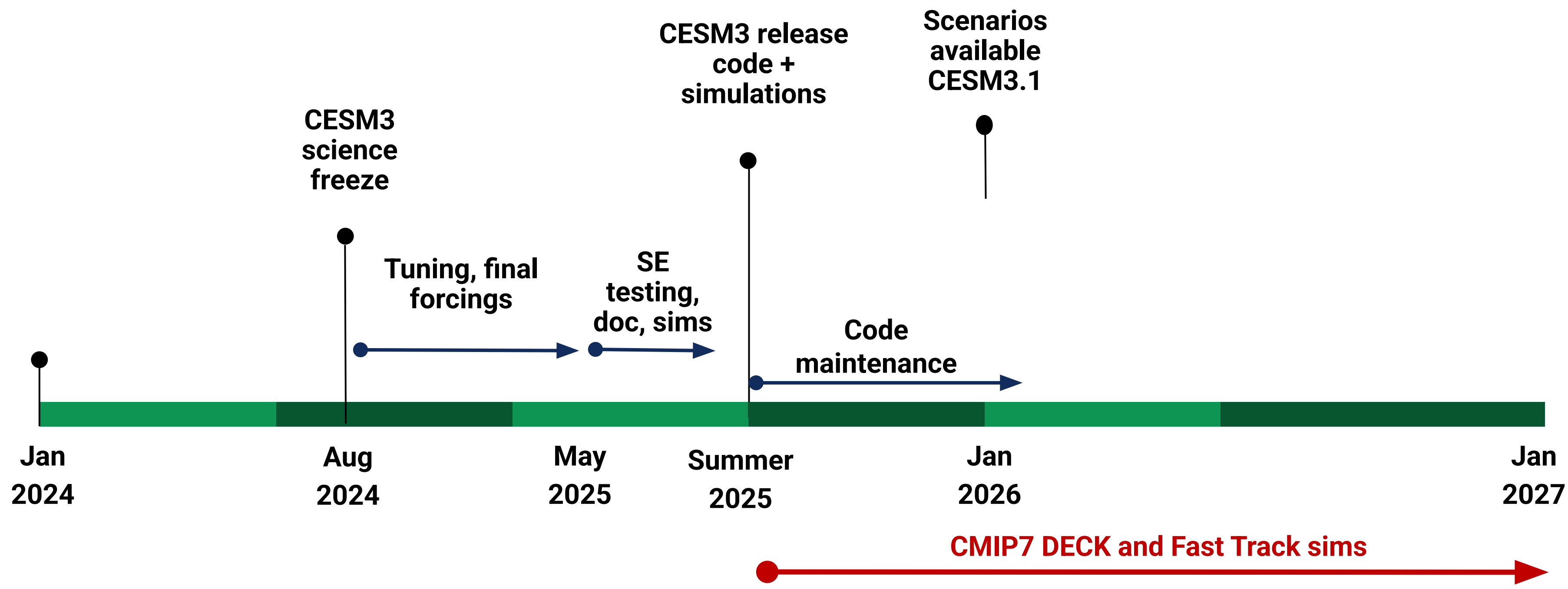
CMIP7 DECK and Fast Track experiments



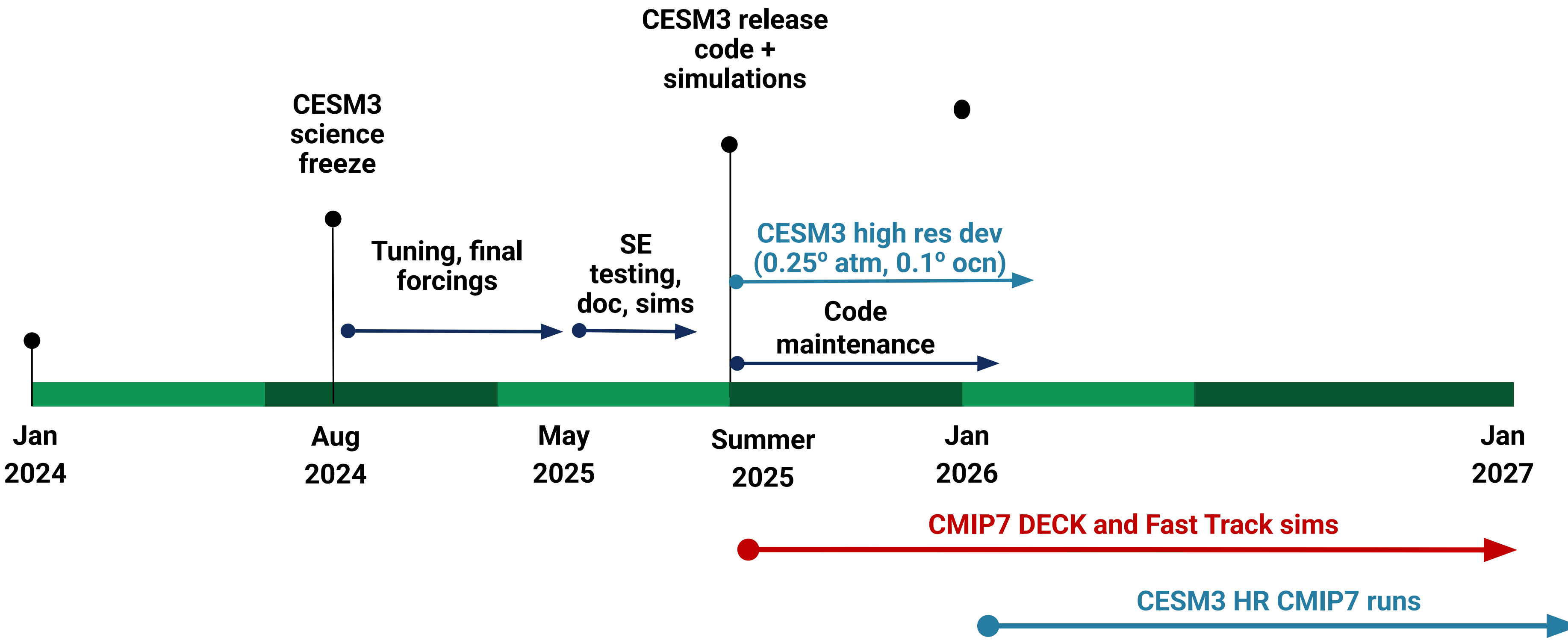
14,000 total years of simulation; CESM3 estimated cost: 14,000 pe-hrs/yr at 12.2myrs/day

196M pe-hrs, 3.2 yrs wall clock

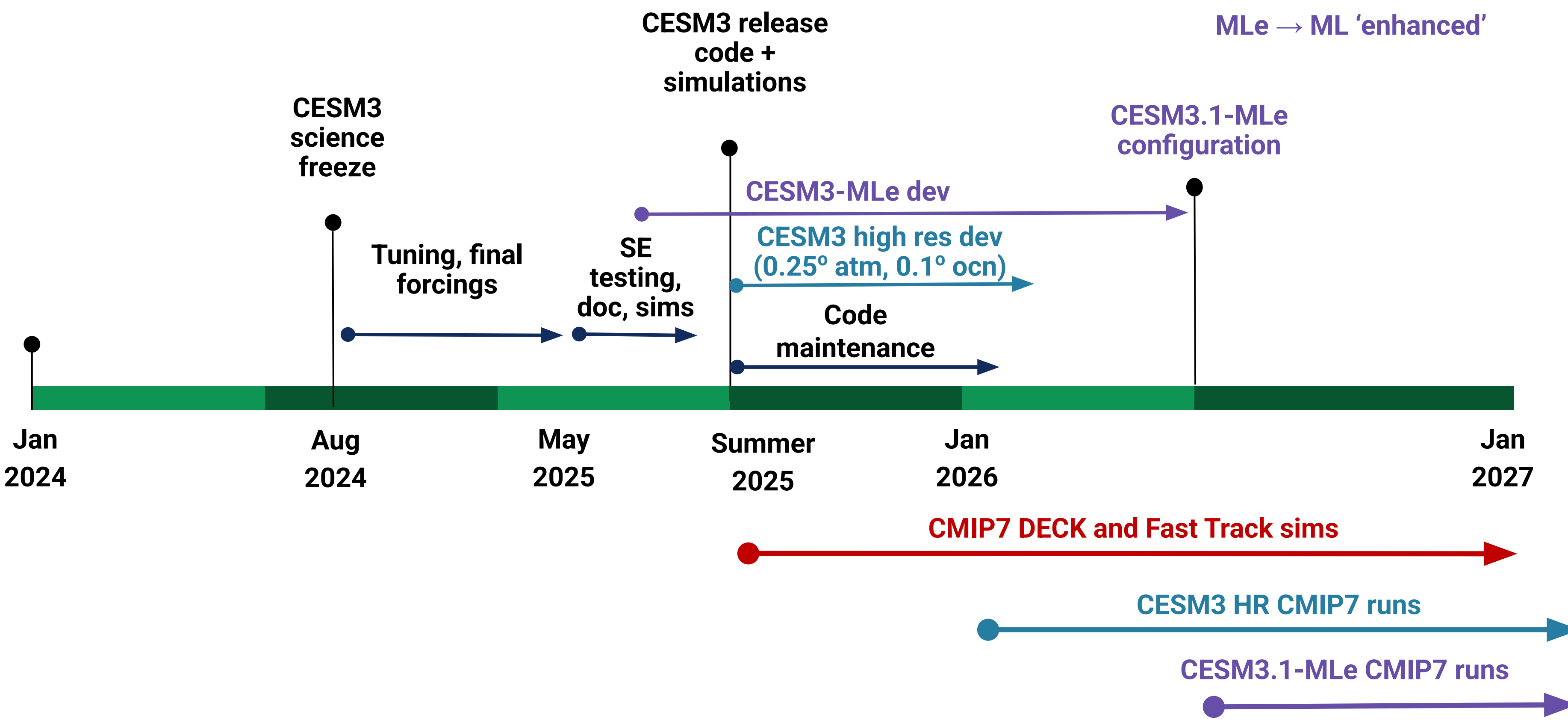
Proposed CESM Timelines



Proposed CESM Timelines



Proposed CESM Timelines



Can we accelerate progress towards more reliable (unbiased) climate projections through production of CESM3-MLe?

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.

Forces that are driving the future of Earth System modeling

- Urgent need for actionable information (climate risks, consequences of intervention/mitigation)
- High-resolution (0.25°) and ultra high-resolution (km-scale) modeling configurations
- Machine learning, hybrid modeling, emulators
- Goal of seamless Earth System Prediction Across Timescales (ESPAT), S2S → S2D → 30-yr projections
- Changing computing architectures → code modernization?
- Calls for improved accessibility of ESMs and output (e.g., to global south)

Image: Getty images

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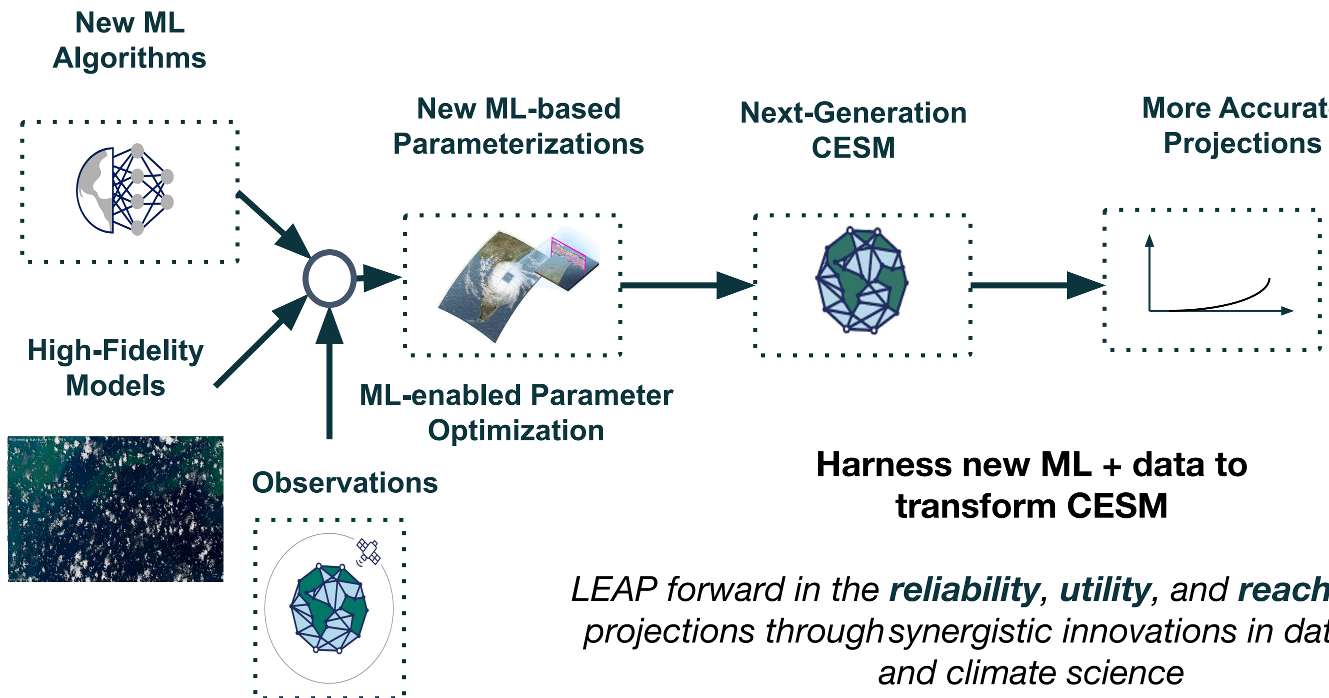

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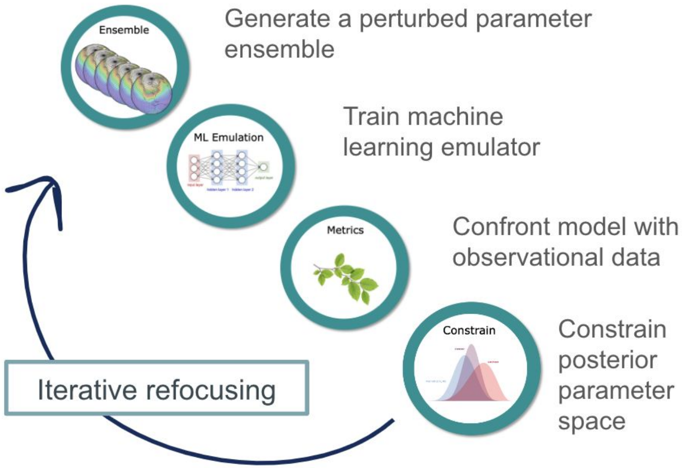
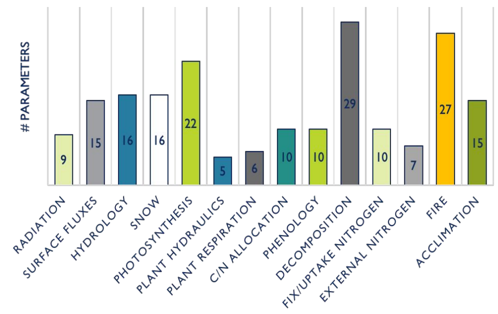


Methods developed by Linnia Hawkins, Daniel Kennedy, and Katie Dagon

Establish systematic ML-based methodologies for calibration of Earth System Model parameters



Large CAM and CLM perturbed parameter ensembles are available

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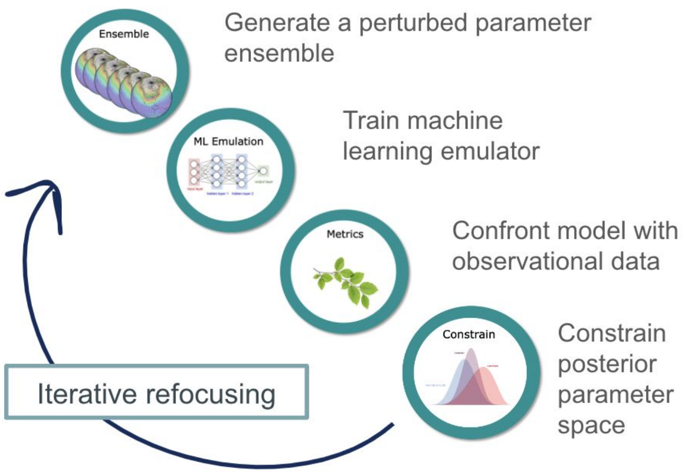
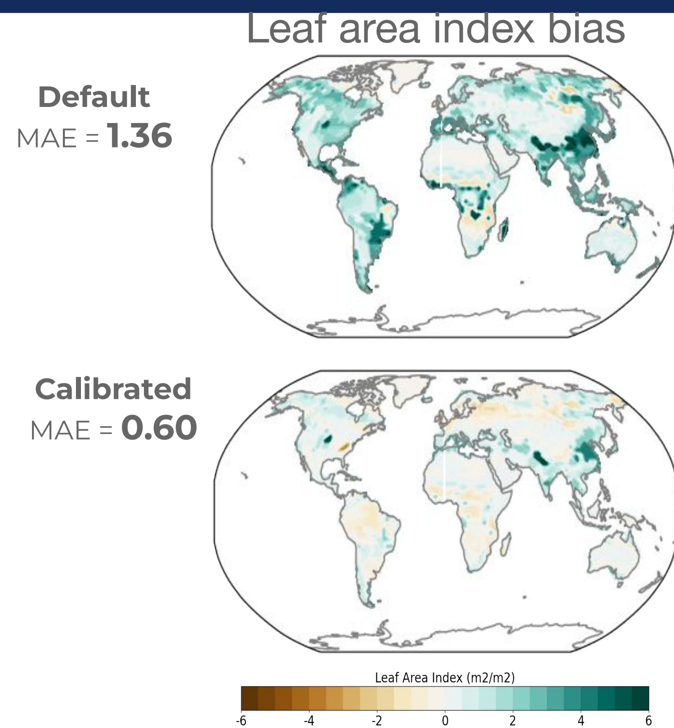


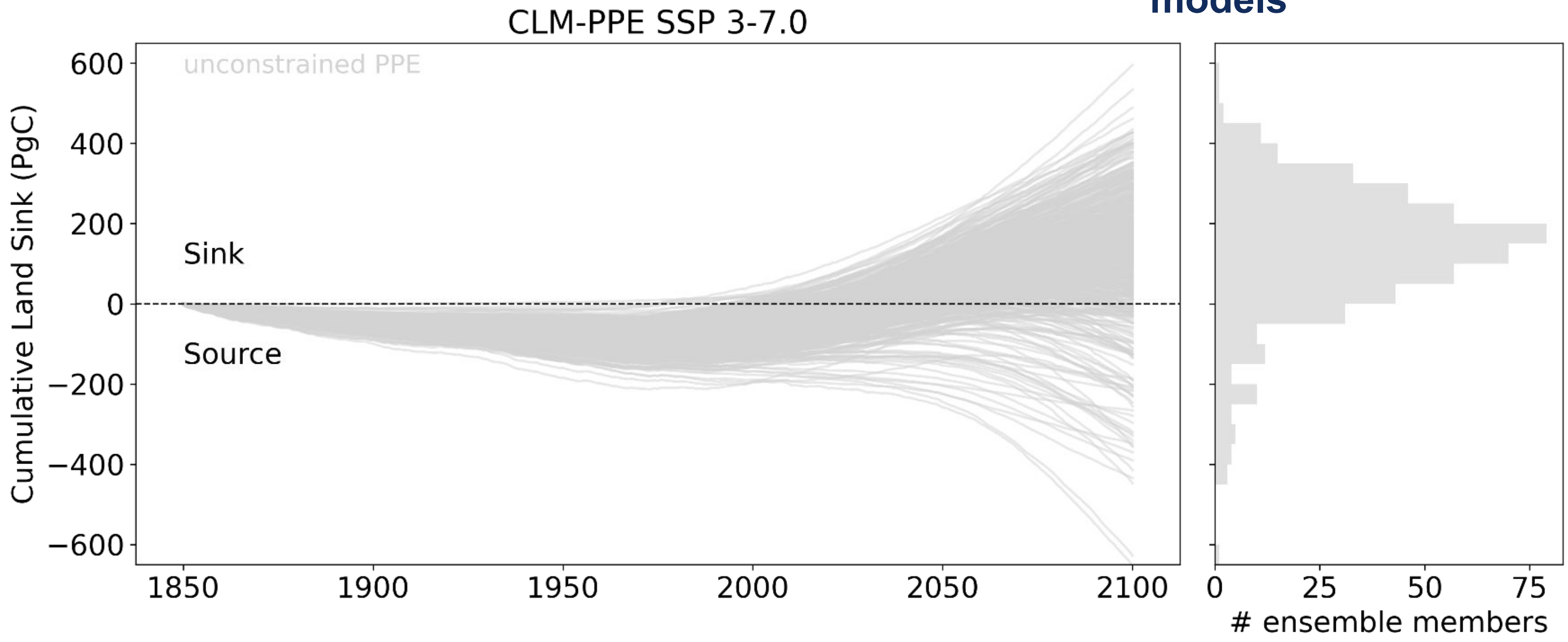
Applying methods now to calibrate CLM6 for CESM3



Constraining land carbon cycle projections

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

Range ±600PgC is as large as across CMIP6 models



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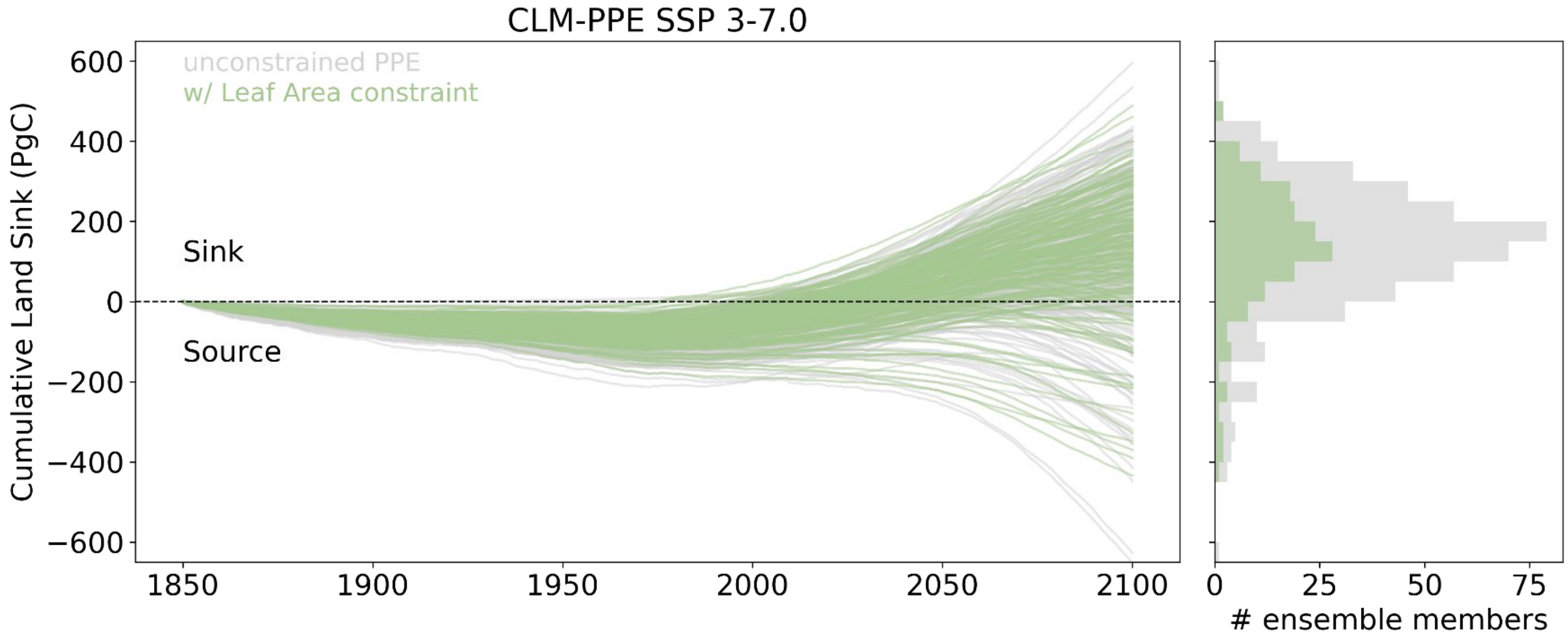

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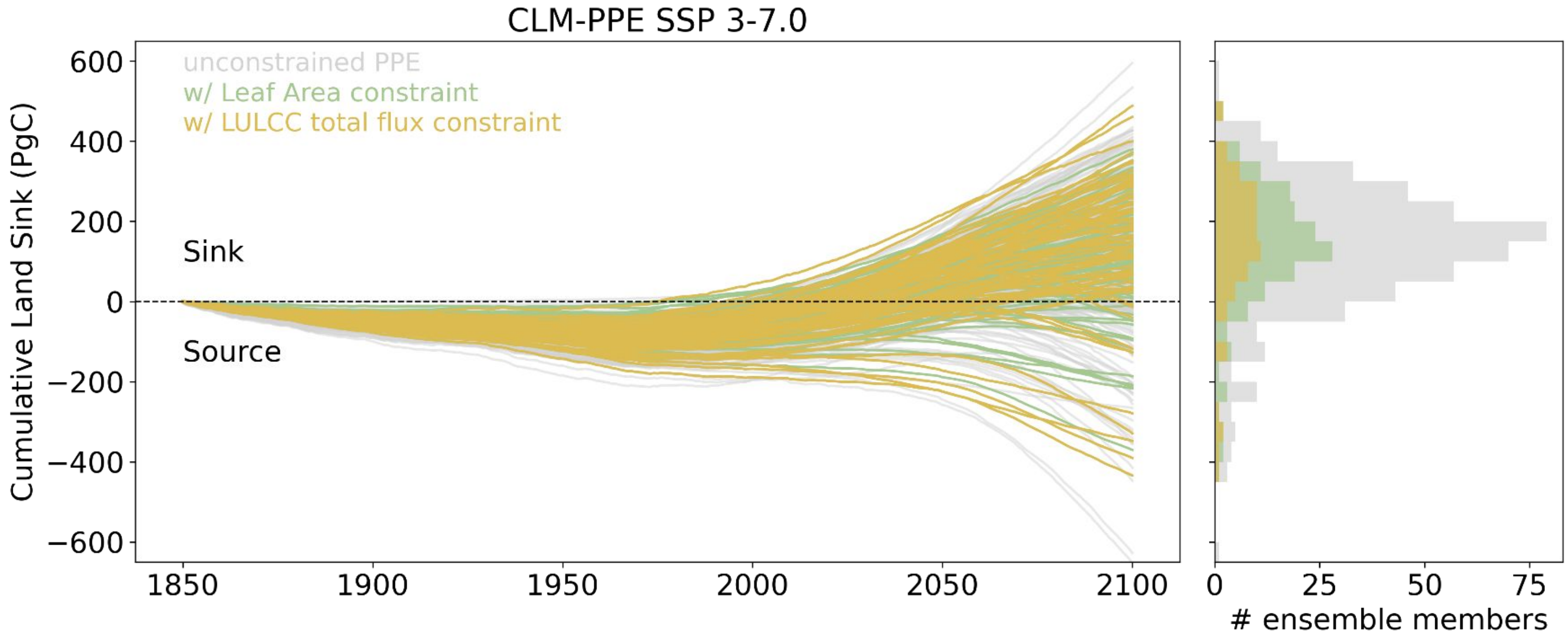
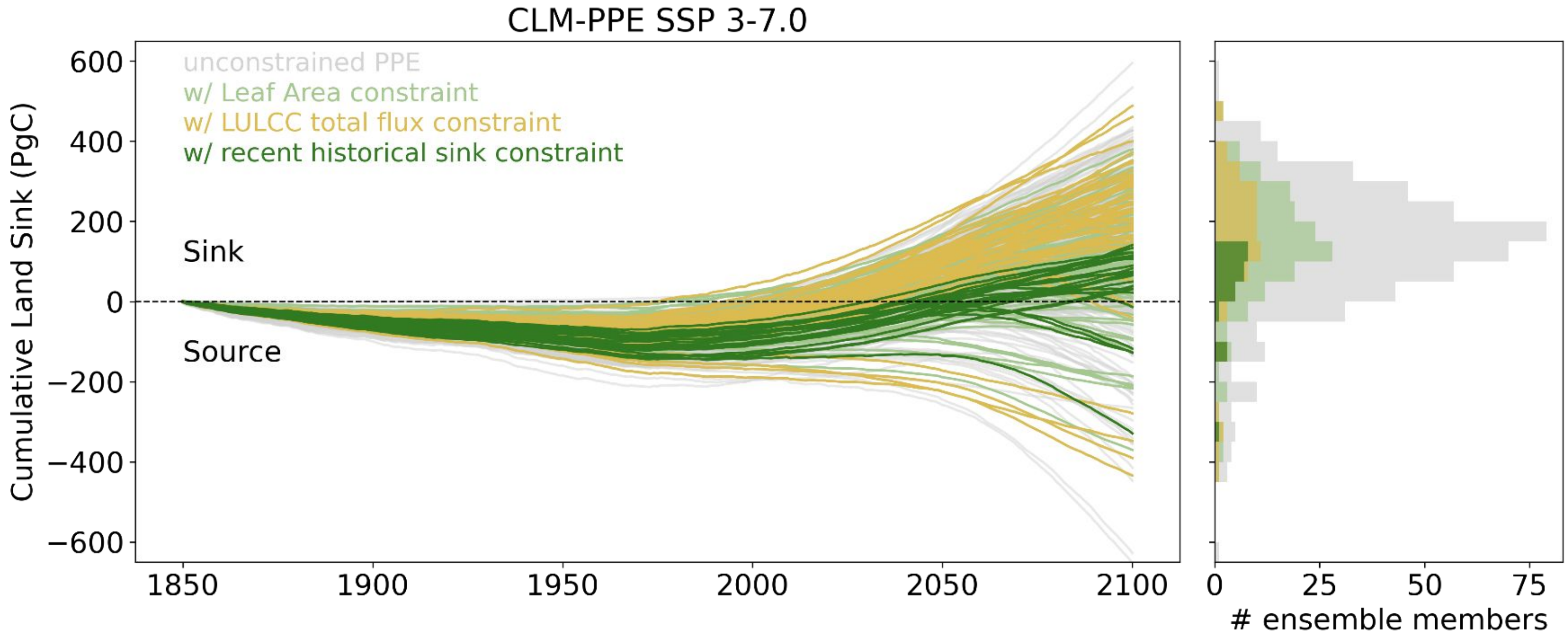


Constraining land carbon cycle projections

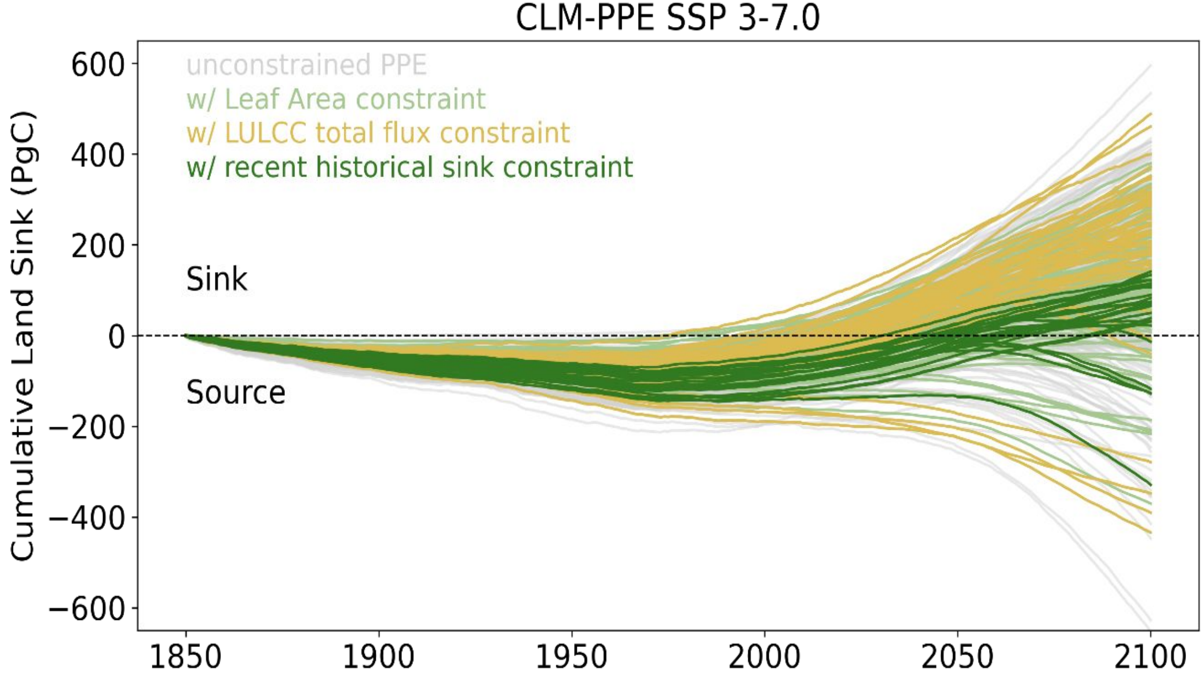
500 land-only simulations with Latin Hypercube generated parameter sets (25 parameters)

Many parameter sets will be consistent with our set of observational constraints
Plan is to select one as default, but



Constraining land carbon cycle projections

500 land-only simulations with Latin Hypercube generated parameter sets (32 parameters)



Still a diversity of carbon trend responses, even in constrained sets

For CLM6, plan is to select one as default, but release many (~50-100?) with the CESM3 release

Can we build an emissions-driven CESM3 Large Ensemble by including multiple land carbon parameter sets to span this uncertainty (in addition to Initial Condition uncertainty)?

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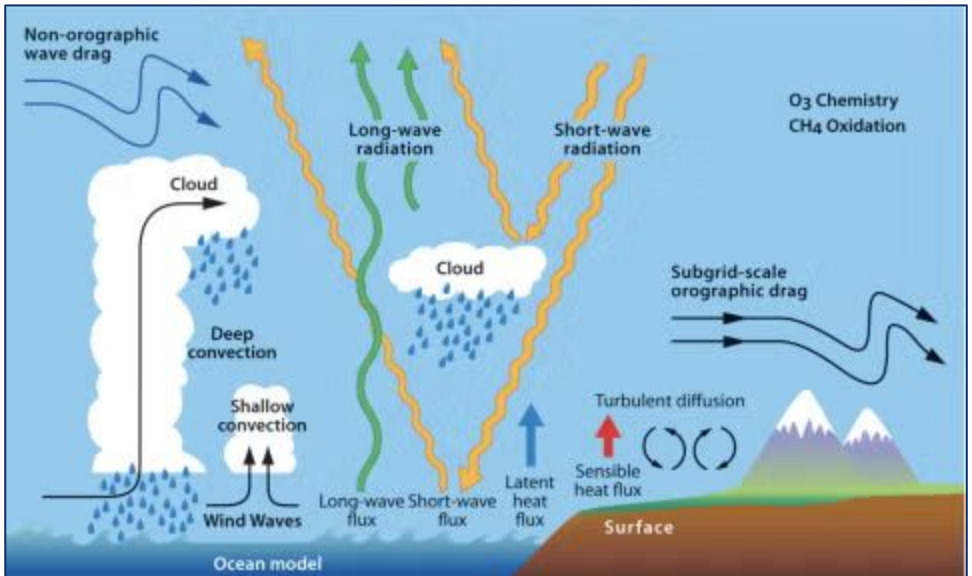
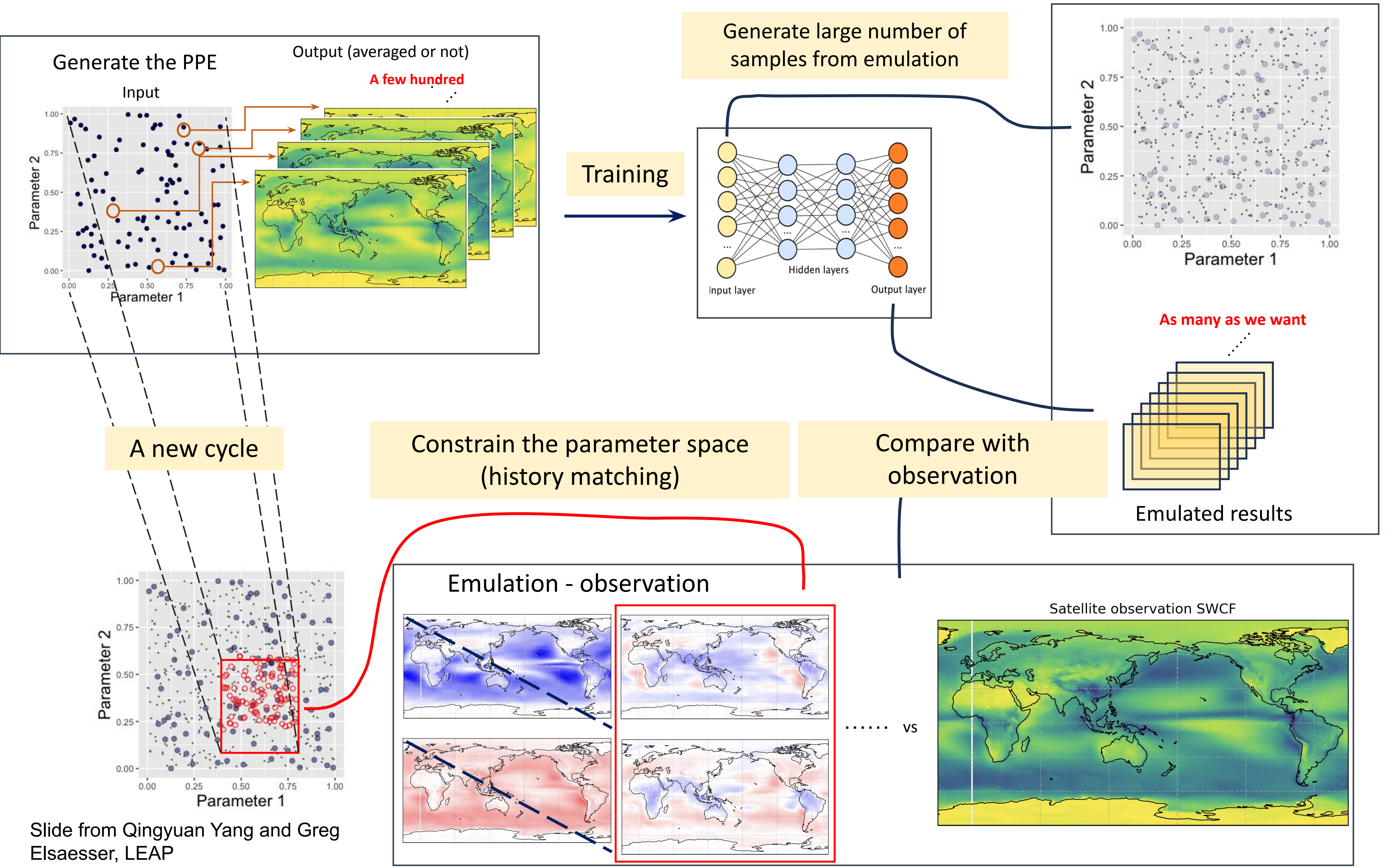


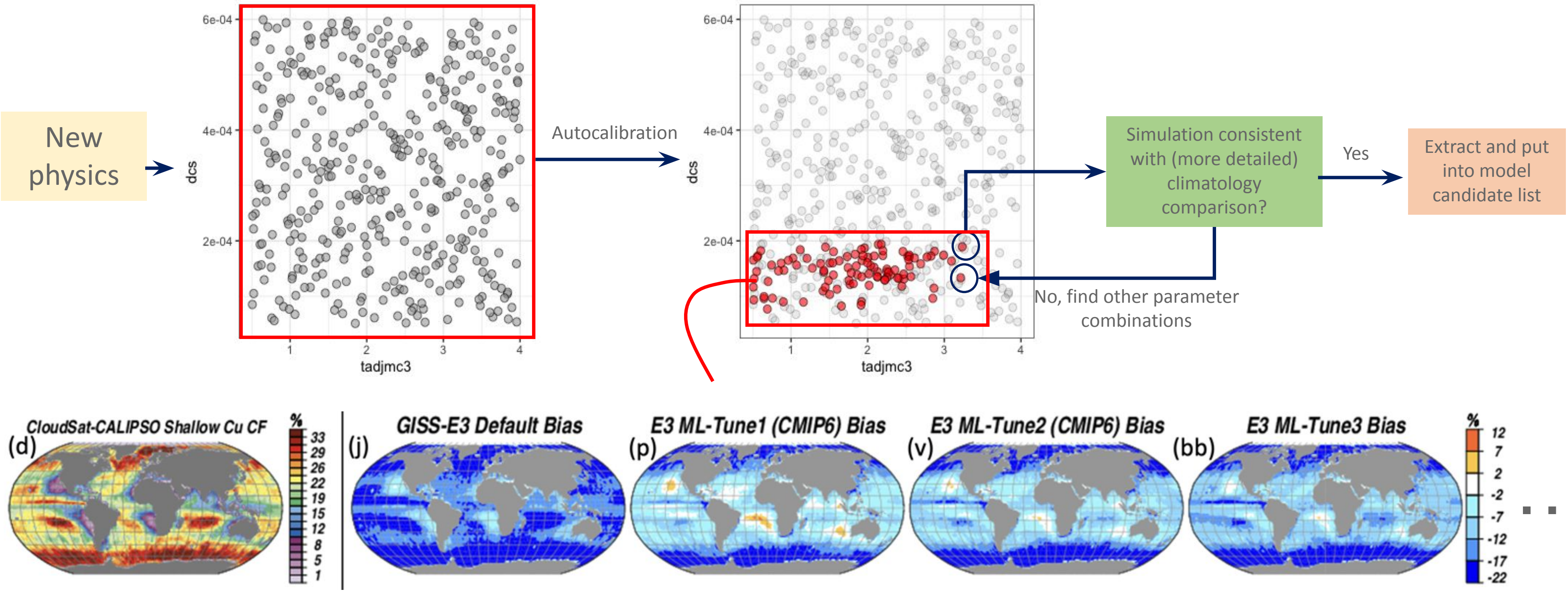
CAM parameter calibration work will draw on combined experiences with GISS model and with CLM calibration

Note: New people resources in place to accelerate effort with CAM7 (Qingyuan Yang and Addisu Semie)



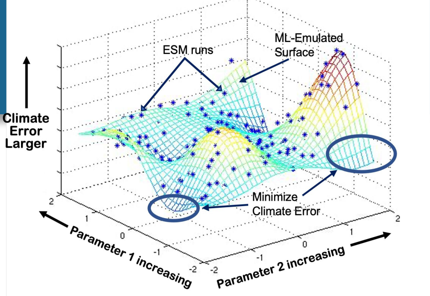
Slide from Qingyuan Yang and Greg Elsaesser, LEAP

Workflow for GISS ModelE3 version and onward…



The bias for the calibrated ensemble members becomes much smaller. Example shown above: for shallow cumulus cloud fraction, where new physics and hand tuning never gave a good answer (previously a -20 to 30% bias in tropics, now -5% in tropics).

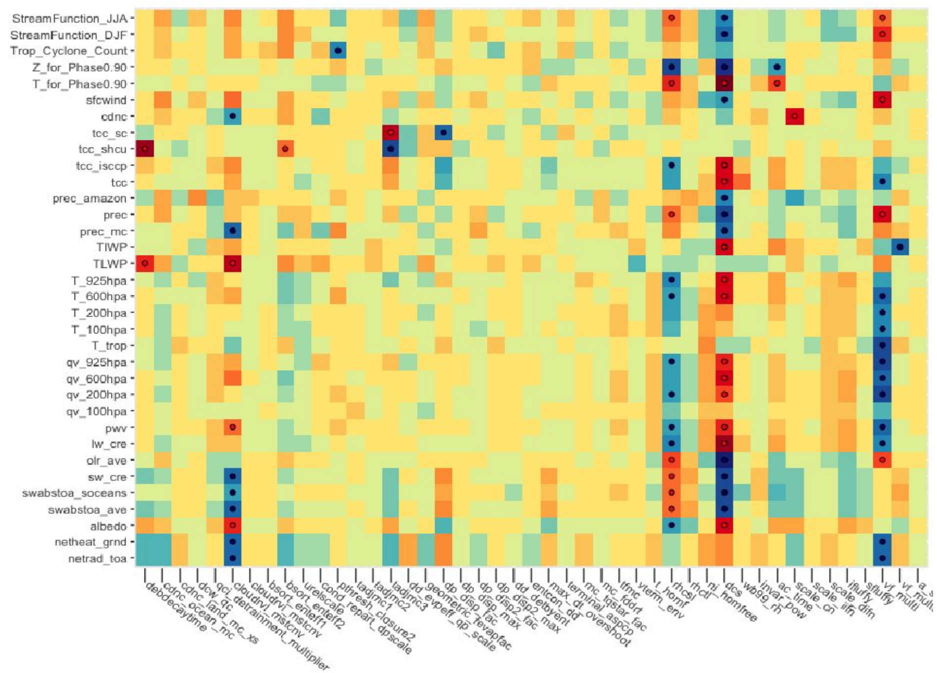
Heat Maps of impact in a PPE vs auto-calibrated ensemble



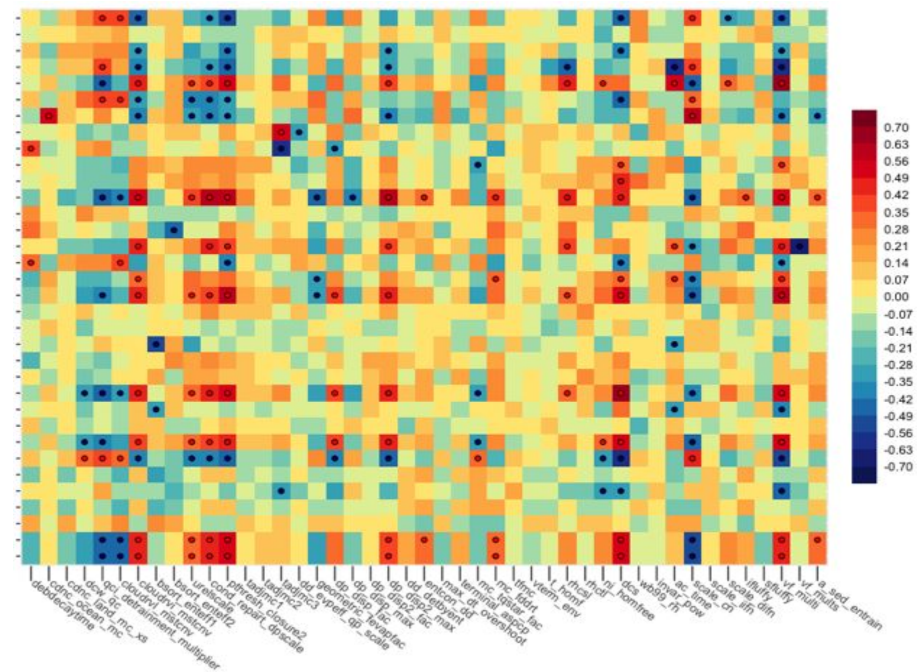
Parameter sensitivities (δoutput / $\boldsymbol{\delta}$parameter) can change as model approaches reality (i.e., less biased mean state)

More parameters matter as you approach the answer!

Perturbed Physics Ensemble (PPE)



Calibrated Physics Ensemble (CPE)



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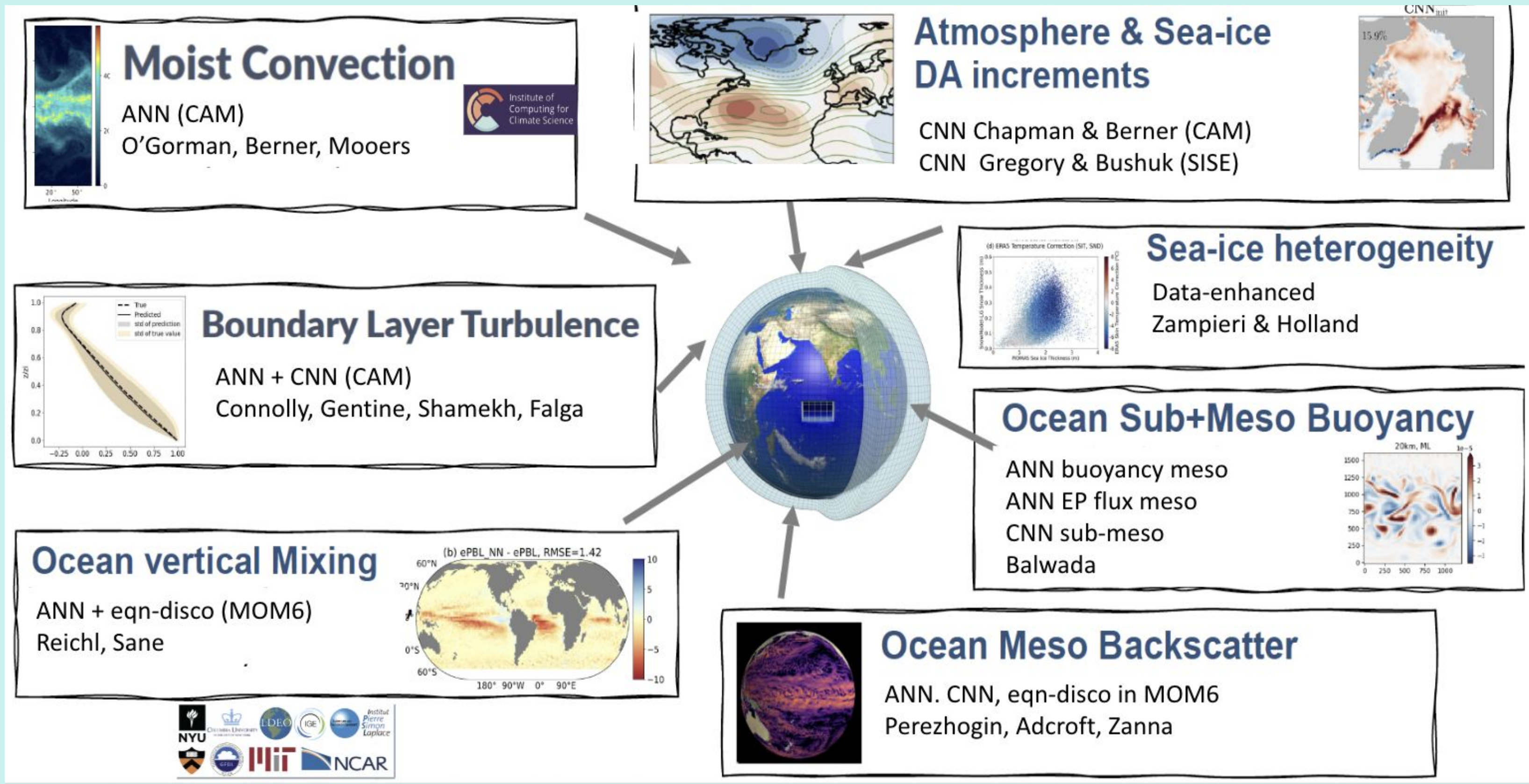

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Parameterization	Description	Likelihood for CESM3-MLe
Warm rain microphysics	TAU bin microphysics neural net emulator	High
Vegetation phenology	Leaf onset and offset equations for Plant Functional Types; equation discovery from satellite LAI and climate indices	Medium-High
Microphysics (Ice)	Ice parameter retrieved with ML based on chamber growth experiments	Medium-High
Microphysics (BOSS)	Multi-structure microphysics parameterization for warm processes	Medium
Air-sea flux	Neural Net based probabilistic model of mean and variance based on in-situ observations	Medium
Superparameterization (V1, convection + radiation + 1-moment microphys)	Embedded cloud resolving models with full land surface and condensate coupling, i.e. ClimSim. Caveat: V1 excludes two-moment microphysics needed for aerosol-cloud interaction.	Medium

Rough estimation of readiness level of LEAP ML parameterizations

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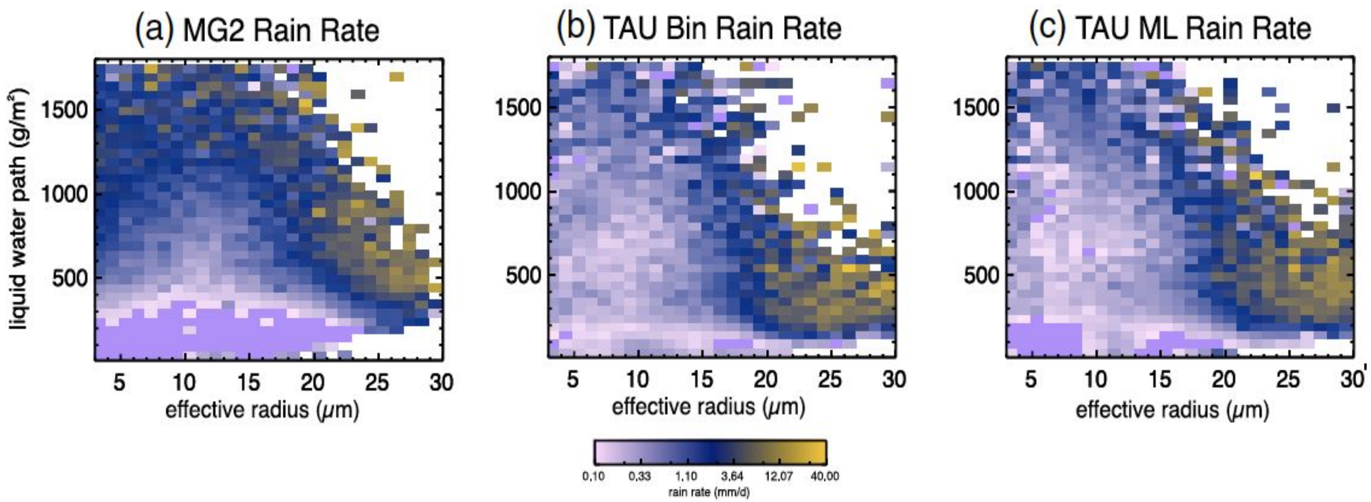
Emulate cloud droplet autoconversion and accretion with NNs trained on CAM simulations with warm rain process replaced with highly resolved bin microphysics (TAU code)



Gettelman et al., (2021)

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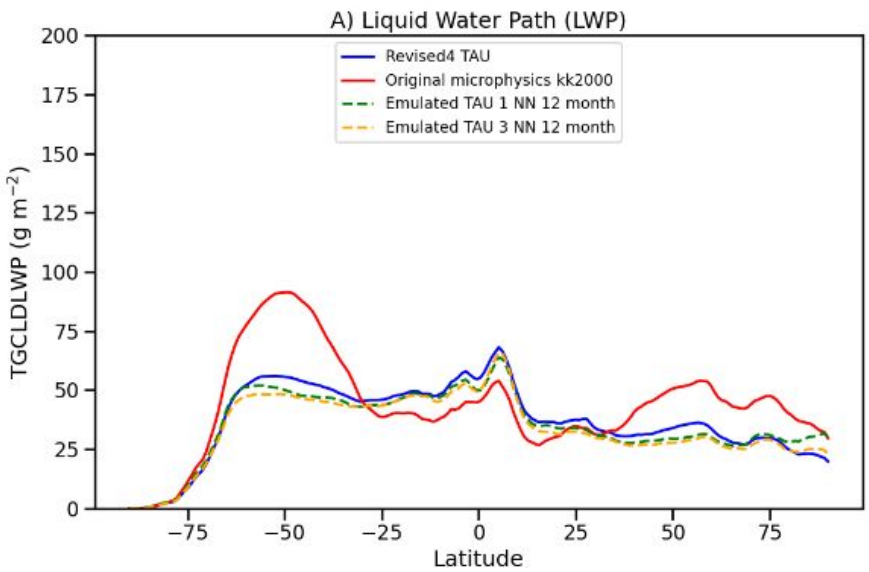

Technical progress / issues

- Neural nets are written in Fortran
- Read a file with the weights+biases from training the NN in Python
- Restricted to the current architecture (feed forward, fully connected neural network)
- A python-fortran bridge would be preferable, because it offloads the hardcoded fortran to a more flexible Python environment

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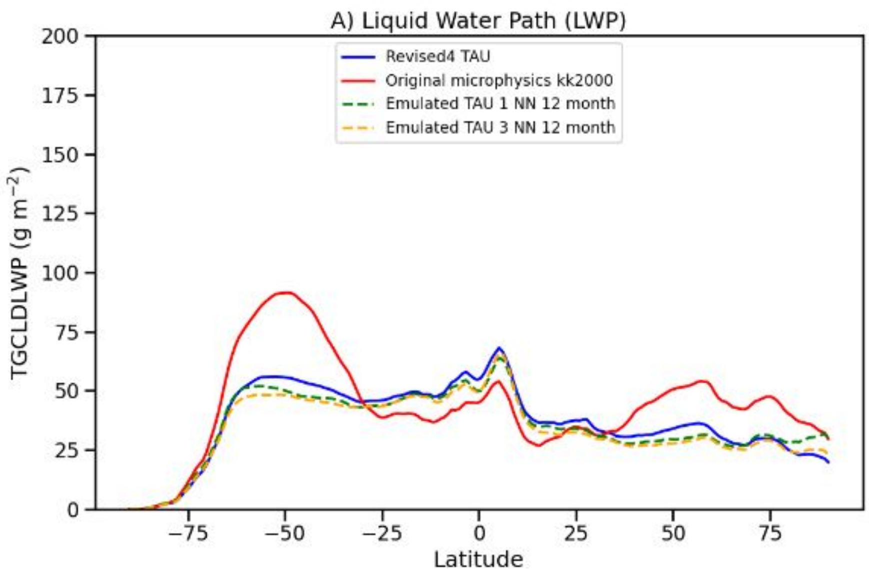


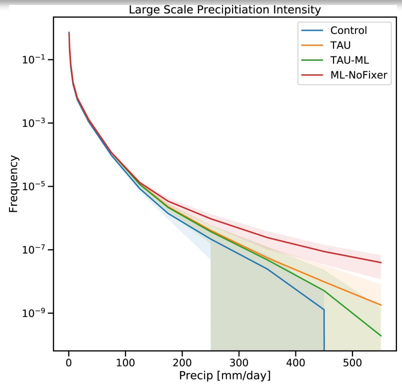
Warm rain tau bin microphysics emulation online in CAM

- Improved precipitation frequency distribution
- Improved agreement with cloud fraction obs in many regions (though not all)
- Cloud fraction and SWCF, for example, are quite different to the control model → climate is quite different in CAM (and presumably CESM, not tested)
- How will this affect aspects of CAM simulations?

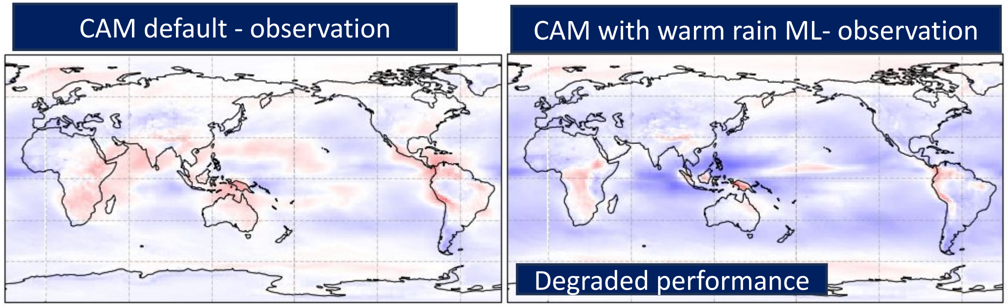
Gettelman et al., (2021)

Developing workflow when new ML-guided physics goes into CAM or CLM (example with ML warm rain micophys)

1. New ML microphysics, improvement in rainfall distribution (orange, green lines)!

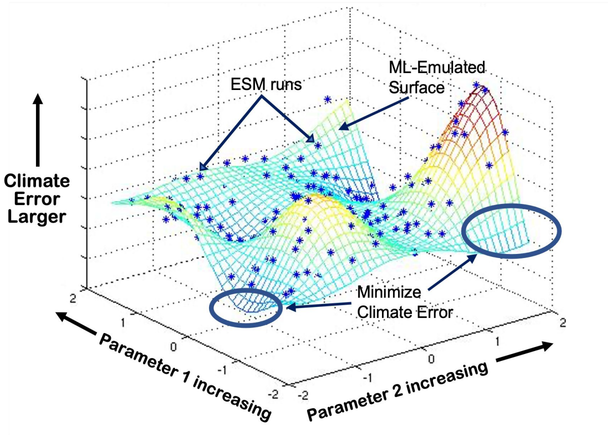


2. Degraded performance can occur for some previously-good climatologies when CAM with warm rain ML is adopted.



Schematic only; representative of a climatological radiation or cloud field

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



Integrating and evaluating in the Community Atmosphere Model

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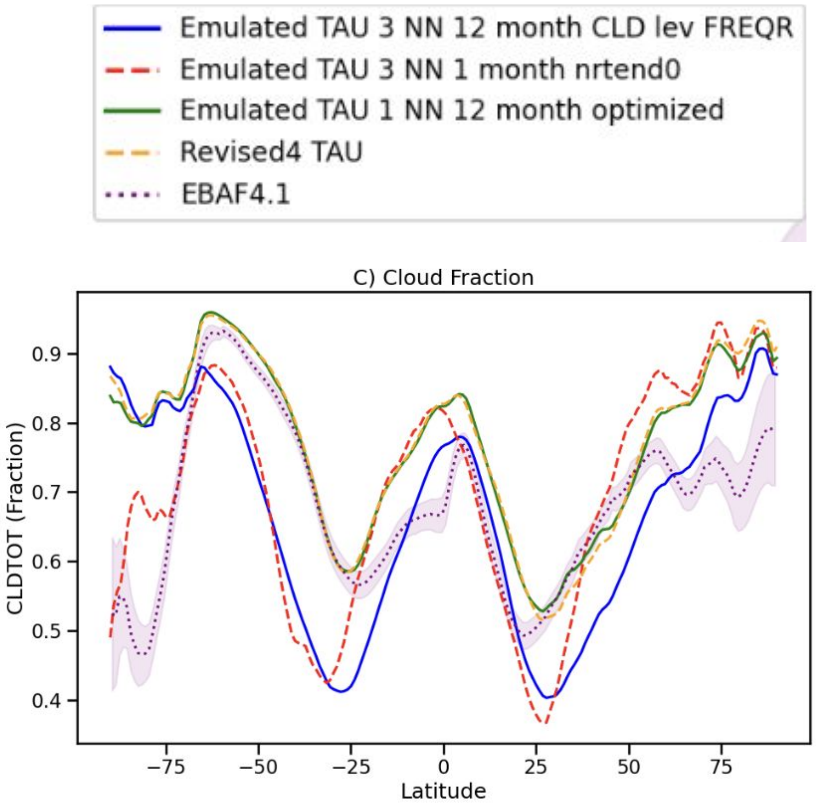

Work by Wayne Chuang and DJ Gagne (LEAP)

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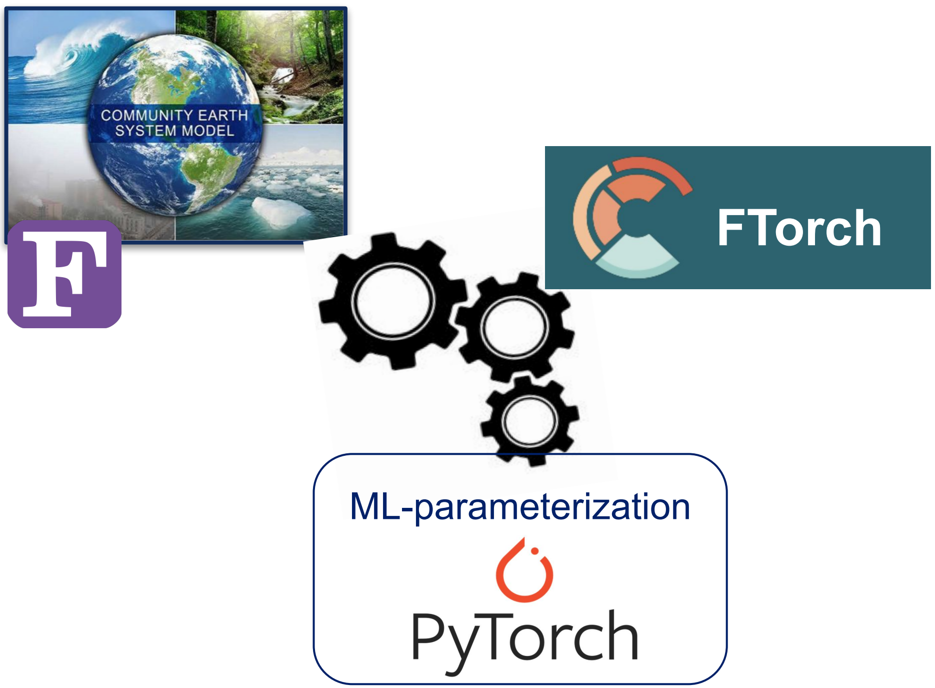
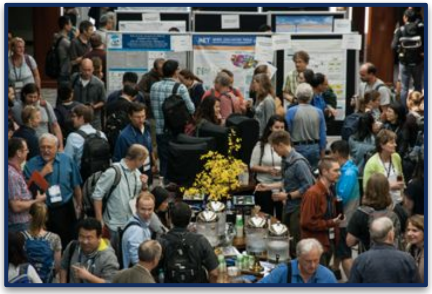


Robust, flexible, and sustainable implementation of ML-based parameterizations requires Fortran-Python bridge

- FTorch implementation with CESM working fairly well (thanks to Will Chapman and Jim Edwards)
- Needs an integration plan to bring fully into CESM3 infrastructure
- Documentation
- Testing, edge case evaluation
- GPU-CPU combo testing
- Ideally, some consistency in use across US modeling centers

So, how do we get to our goal of a CESM3-MLe?



Collective effort, engagement, and focus (LEAP, M²LINeS, CESM core team)

- More dedicated resources now in place
    - **Integration Team: Linnia Hawkins, Addisu Semie, Qingyuan Yang (LEAP); Will Chapman, Xavier Levine (M²LINeS); Juliene Savre-Piou (ICON-ML)**
    - When CESM3 is complete, more resources/effort from CESM core team
- Integration Team is starting to meet regularly
    - A first task is a survey of candidate parameterizations to fully characterize applicability to CESM, readiness level, needs going forward, timeline, etc
    - ML Integration github (github.com/leap-stc/Integration_team)

Status Update – Parametrizations at GFDL & NCAR

	Data/ML tool	Implementation	Idealized config	Global Config	Misc
Lateral momentum meso	CNN	SmartSim + Forpy	✅	✅	Global model - Dev only 1 year
	ANN	Fortran	✅	✅	OM5 + OM4- same as eqn disco for the NA and no changes for the SO
	Equation Discovery	Fortran	✅ (NEMO + MOM6)	✅	OM4: reduce biased in North Atlantic but not Southern Ocean
Lateral buoyancy meso	ANN	Fortran	✅	July 2025 OM4	
buoyancy + mom combined	ANN	Fortran	✅	No immediate plans	
Sub-meso	CNN			No plans	To be tested in NEMO
Vertical Mixing	ANN + Eqn Disco	Fortran	—	✅	Tested in GFDL SPEAR coupled O+A+I To be tested within KPP CESM (TBD)
Waves	ANN	TBD	—	OM5/CM5 Planned (pending new hire)	
Moist convection	ANN	Fortran	In progress CAM In progress SCAM+ aquaplanet	July 2025 (TBC)	
Atm Boundary Layer	CNN + ANN	Fortran+ Ftorch	Planned start Dec 2024		Idealized Online setup to be tested with CAM
Sea-ice heterogeneity	Obs-based	Fortran	—		CESM

Summary: Towards a CESM3-MLe

- **Push forward (now) so we can test the hypothesis that ML can help build better and more accurate ESMs for adaptation and mitigation needs**
  - Sustained team interactions (e.g., PI, ML-param developer, experienced CESM developer, and SE)
  - More coordination / communication (github CESM-MLe project management)
  - More software engineers needed

- **Anticipate that there will be challenges**
  - ML params and out-of-training climates
  - Model instabilities
  - Unanticipated interdependencies
  - Substantially new simulated climate that may degrade orthogonal aspects of simulation
  - New tuning challenge with some tuning knobs removed?

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Set a low bar

CESM3-MLe success could be defined as low as 3 to 5 ML-based parameterizations (1-2 atm, 1-2 ocn, 1 lnd, 1 sea ice) along with ML parameter calibration (lnd, atm)

Thank you!