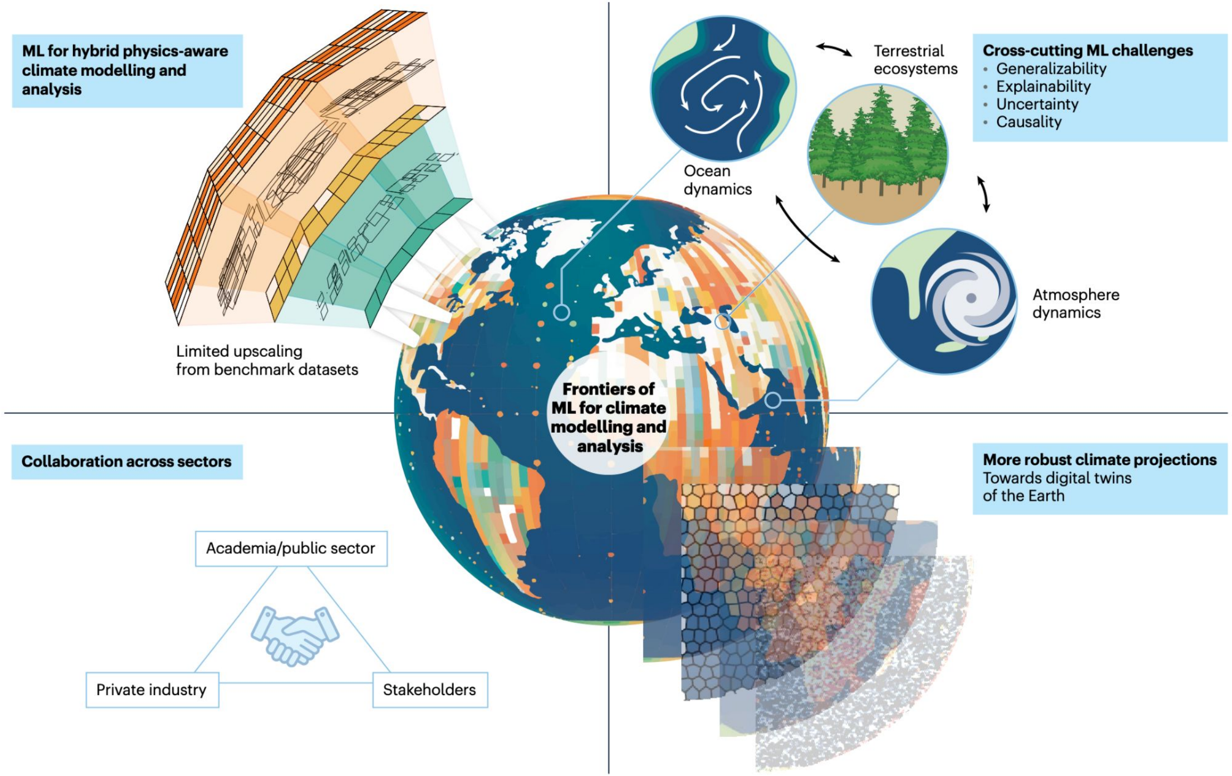
Machine Learning with CESM

Katie Dagon

With contributions from: Charlie Becker, Will Chapman, Nihanth Cherukuru, Da Fan, D.J. Gagne, Linnia Hawkins, Aiden Janney, Teagan King, Dave Lawrence, Aya Lahlou, Xavier Levine, Yuanpu Li, Kirsten Mayer, Brian Medeiros, Pavel Perezhogin, Addisu Semie, John Schreck, Yingkai Sha, Christine Shields, John Truesdale, Qingyuan Yang

CESM Tutorial 2026
July 10, 2026

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)]()

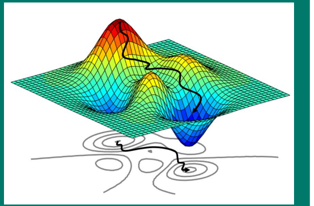
Machine Learning with CESM

HYBRID MODELING

Incorporating ML parameterizations into CESM

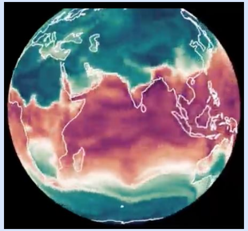
PARAMETER CALIBRATION

Calibrating CESM parameters with ML



EMULATION

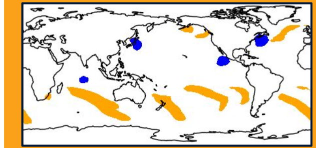
Auto-regressive emulation of CESM and component models with ML



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!

Machine Learning with CESM: Today's Lecture

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Incorporating ML parameterizations into CESM

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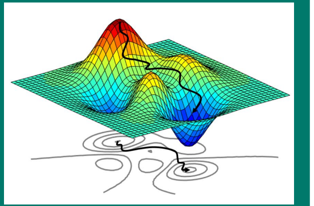
Calibrating CESM parameters with ML



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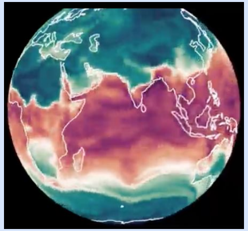

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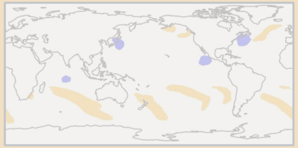

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Machine Learning with CESM: Hybrid Modeling

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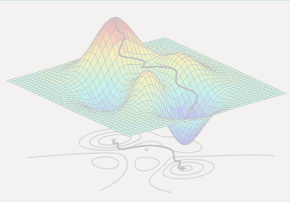

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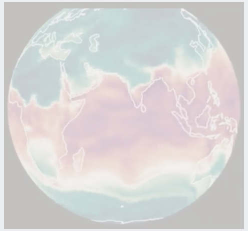

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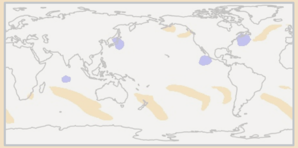

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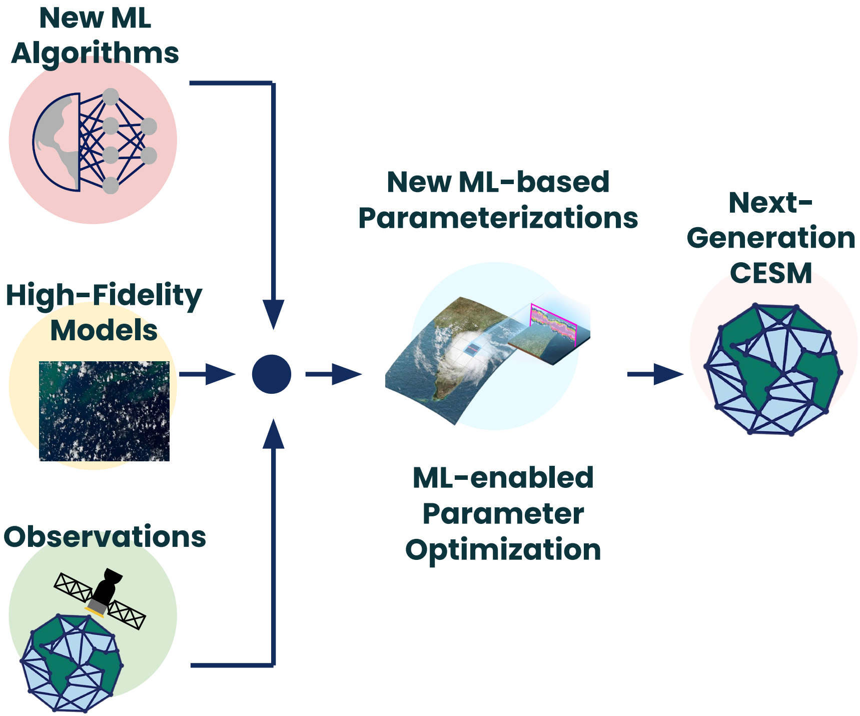
...and more!

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

M²LInES

Other

Radiation

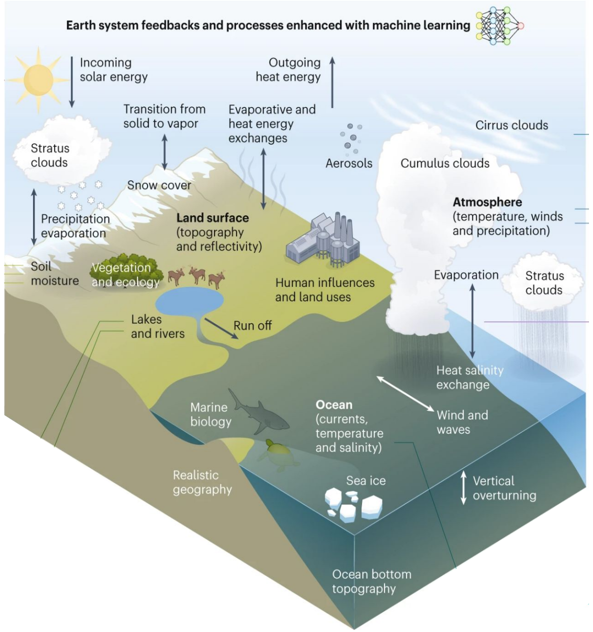
Phenology

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]

Parameterizations in Development for CESM3-MLe

LEAP

M²LInES

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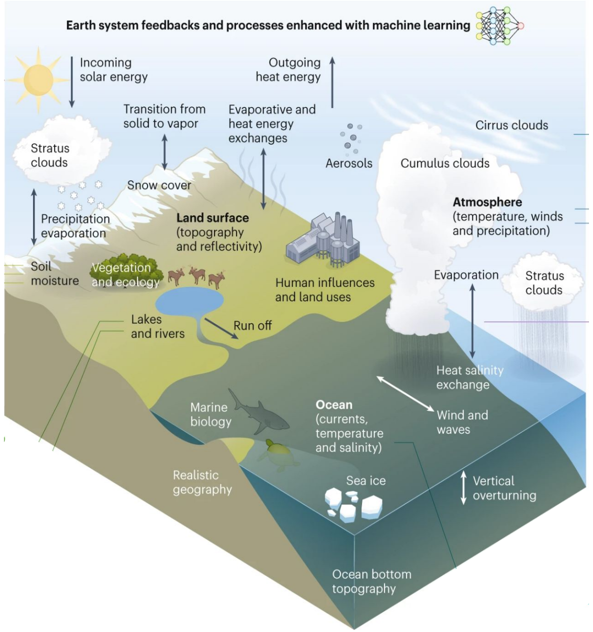

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Figure modified from [Eyring et al. 2024]

Cloud processes are critical and uncertain

- The formation of warm rain is important for cloud lifetime and radiative effects
- Traditionally this processes has been heavily parameterized
- Machine learning provides an opportunity for an alternative approach

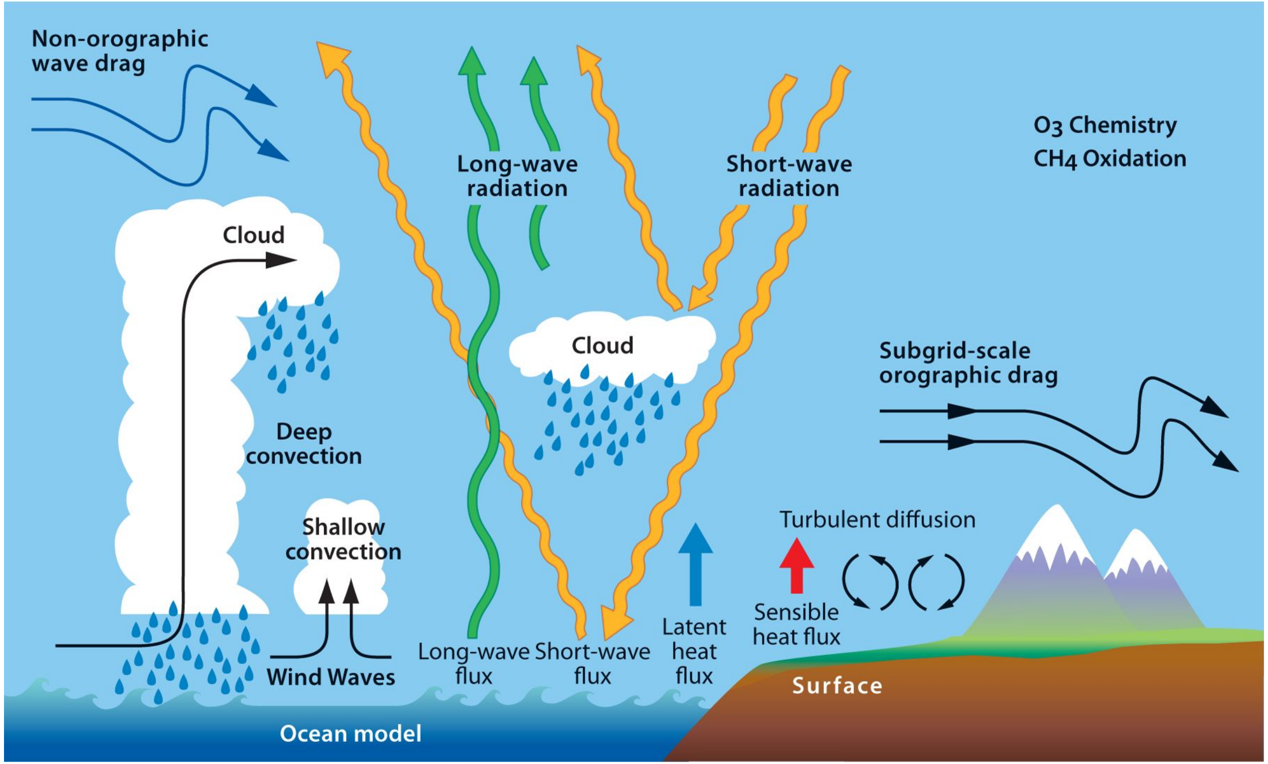


Figure from ECMWF

ML for Warm Rain Microphysics

Traditional Approach

Khairoutdinov & Kogan 2000 (KK2000)

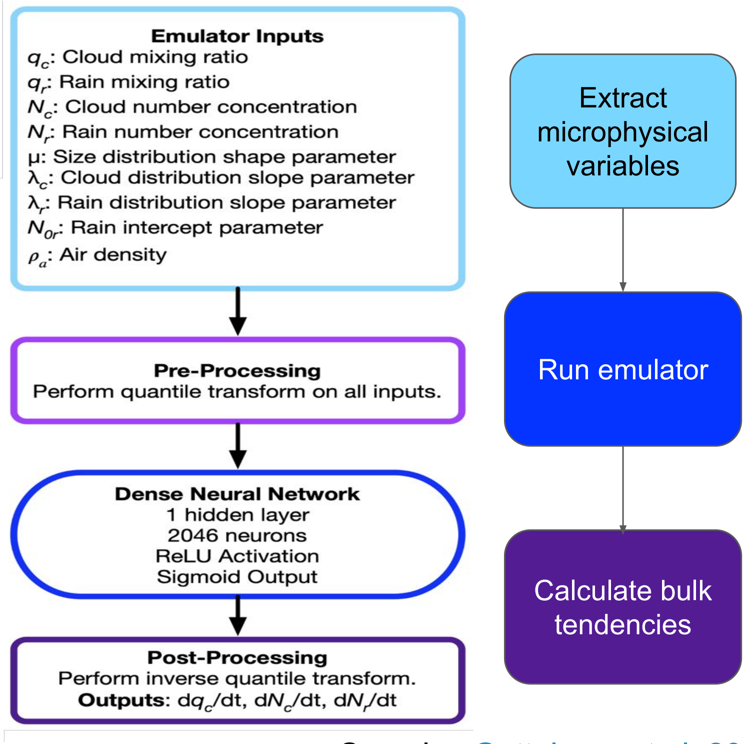
$$\left(\frac{\partial q_r}{\partial t}\right)_{AUTO} = 13.5 q_c^{2.47} N_c^{-1.1}$$

$$\left(\frac{\partial q_r}{\partial t}\right)_{ACCRE} = 67 (q_c q_r)^{1.15}$$

Warm rain is represented by empirical equations for autoconvertion (*AUTO*; transition of cloud drops to rain) and accretion (*ACCRE*; collection of cloud drops by larger rain drops falling).

ML Approach

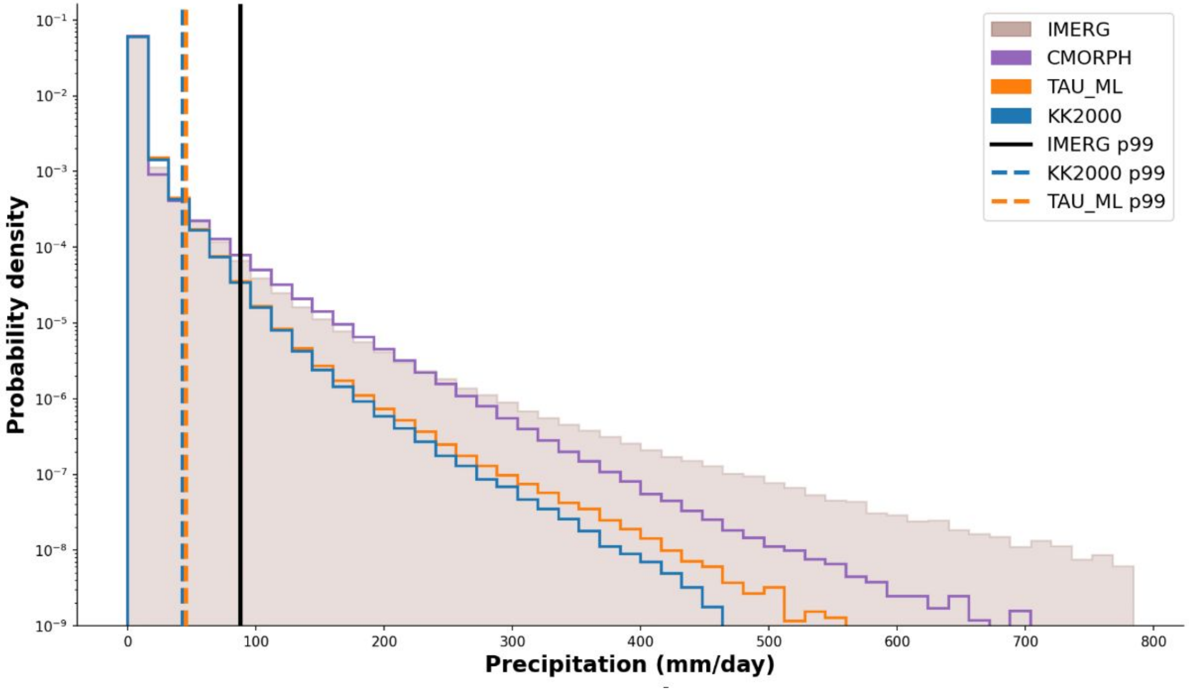
Emulating with the TAU bin model (TAU_ML)



See also [Gettelman et al. 2021]

ML for Warm Rain Microphysics

Develop offline ML parameterization, then test online in CAM

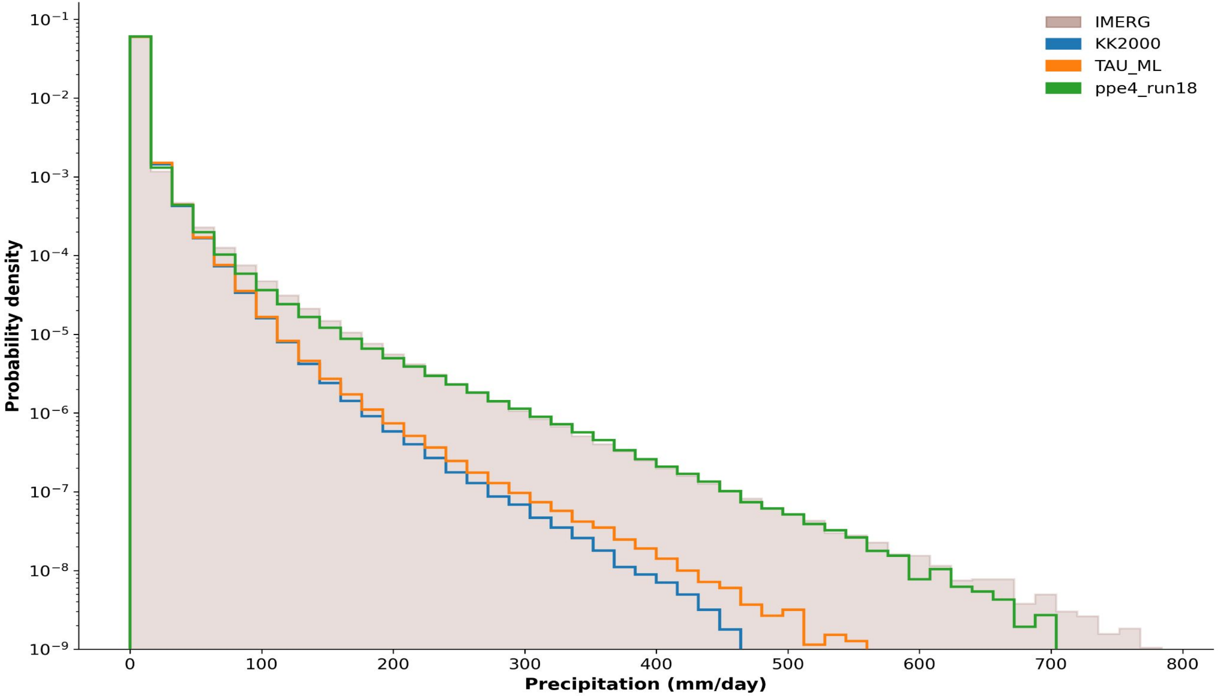


- TAU_ML better matches the observed precipitation distribution (IMERG, CMORPH) relative to the traditional method (KK2000)
- But it still underestimates the most extreme precipitation

Slide from Addisu Semie

ML for Warm Rain Microphysics

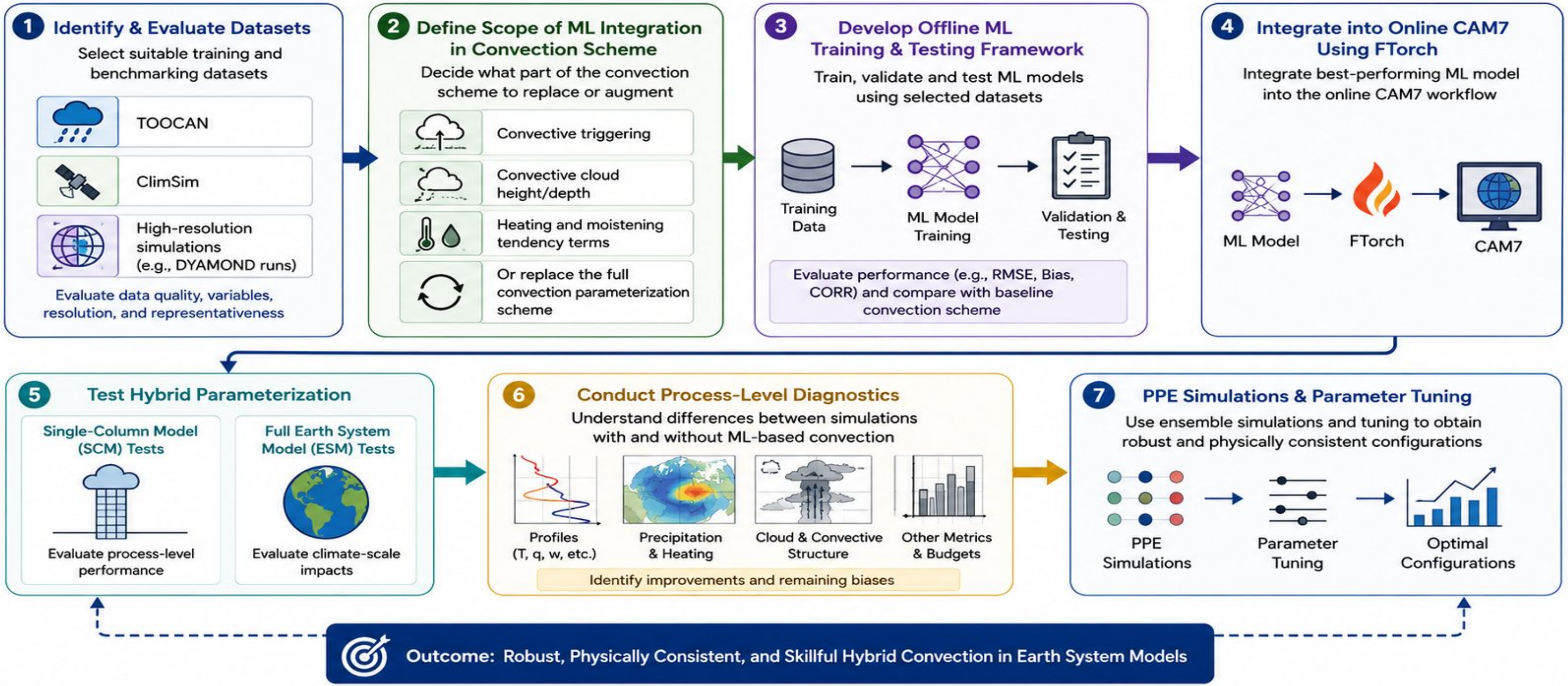
Use parameter calibration to look for improved representations



- Use perturbed parameter simulations (PPEs) to sample different parameter configurations of **TAU_ML**
- Identify parameter configurations that improve representation of precipitation extremes (**ppe4_run18**)

Slide from Addisu Semie

CESM-MLe Workflow



Slide from Addisu Semie

Implementation of ML-based Parameterizations

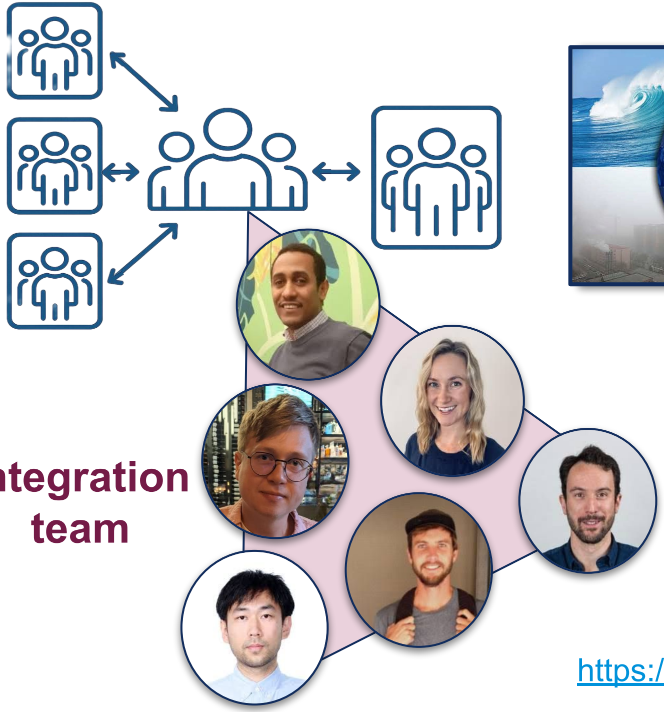
Build robust, flexible, and sustained interactions between ML projects and CESM scientists and developers.

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

LEAP

M^{2}LInES

USMILE



Integration team

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

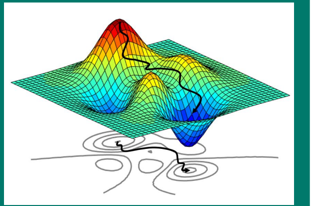
Machine Learning with CESM: Parameter Calibration

HYBRID MODELING

Incorporating ML parameterizations into CESM

PARAMETER CALIBRATION

Calibrating CESM parameters with ML



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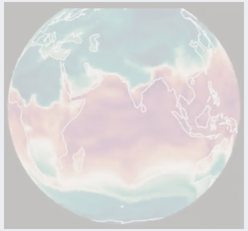
Auto-regressive emulation of CESM and component models with ML



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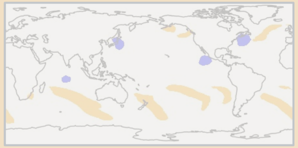

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...and more!

Challenges of “hand tuning”

- **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

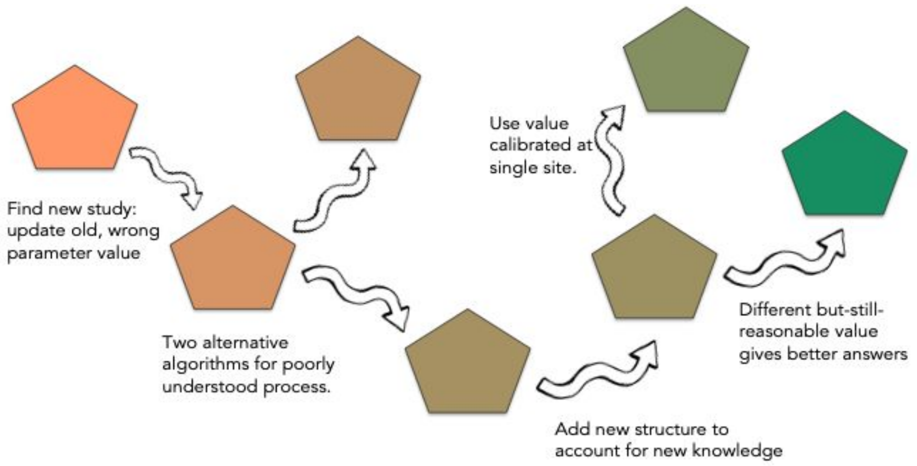


Figure from Rosie Fisher

Systematic Parameter Calibration with ML

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

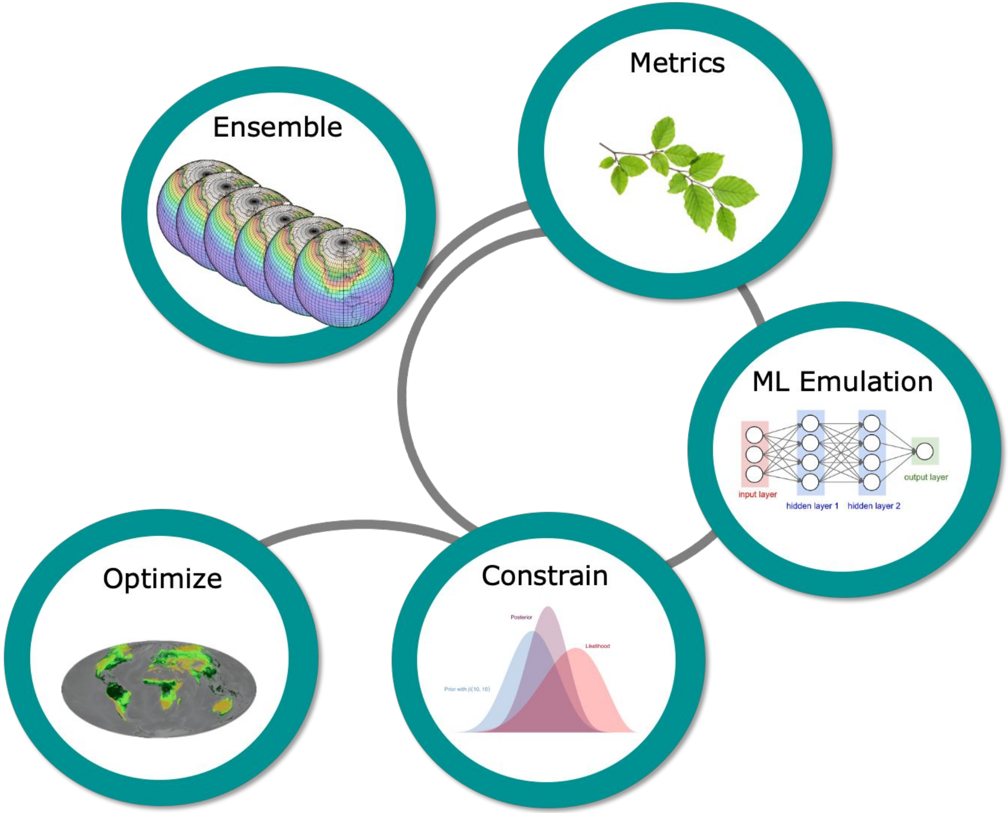


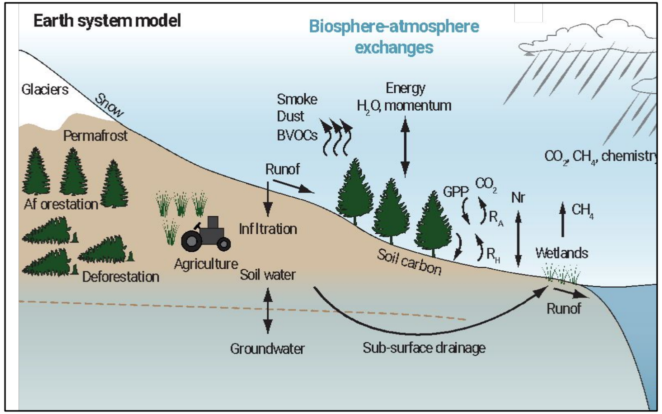
Figure from Linnia Hawkins

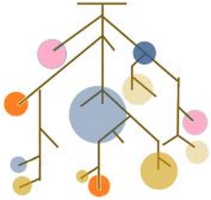
Training the Emulators

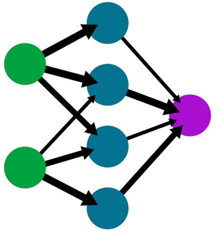
Input: CESM **parameter values** used to generate a perturbed parameter ensemble (PPE)

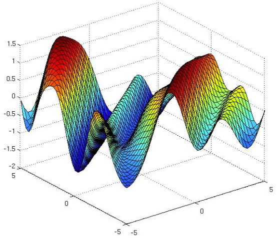
Machine learning emulator *(e.g., neural network (NN), random forest, gaussian process (GP))*

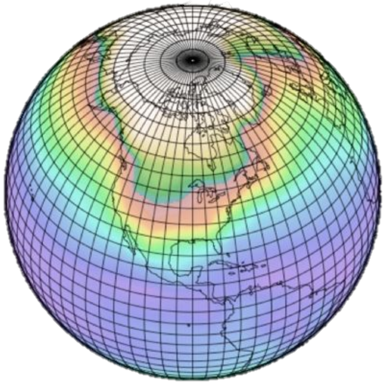
Output: **variable/metric** of interest from the PPE simulation output







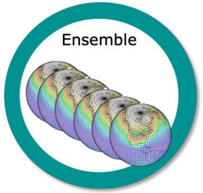




Learning the parameter response functions

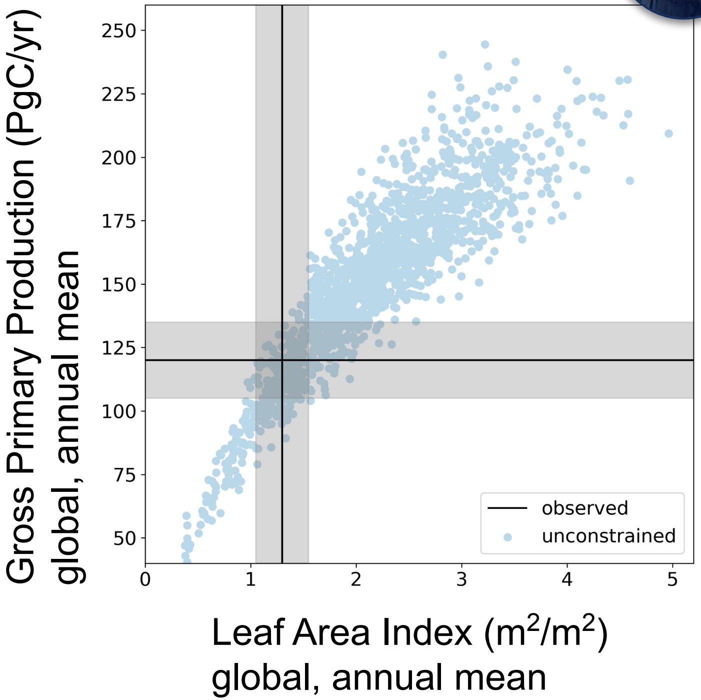
CLM5: Dagon et al. (2020), Kennedy et al. (2025); CLM6: Hawkins et al. *in prep*
CAM6: Eidhammer et al. (2024); CAM7 tuning uses method from Larson et al. (2025)

Constraining Land Parametric Uncertainty



Generate a perturbed parameter ensemble

- Pick parameters of interest
- Sample them across their uncertainty ranges



Hawkins et al. *in prep*

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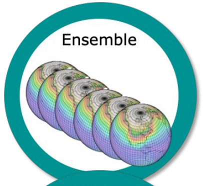

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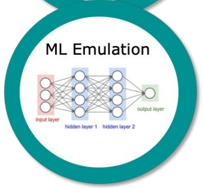
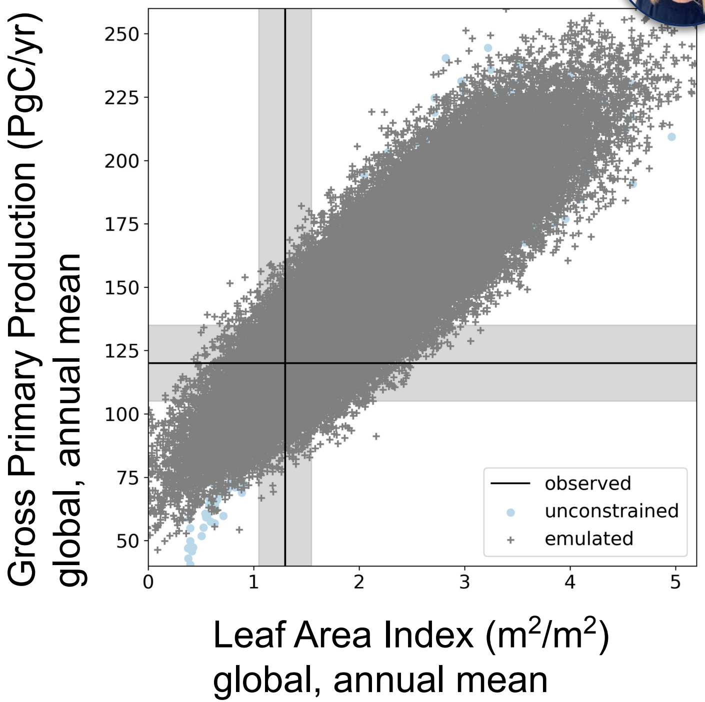


Train machine learning emulator

Emulate a dense sample



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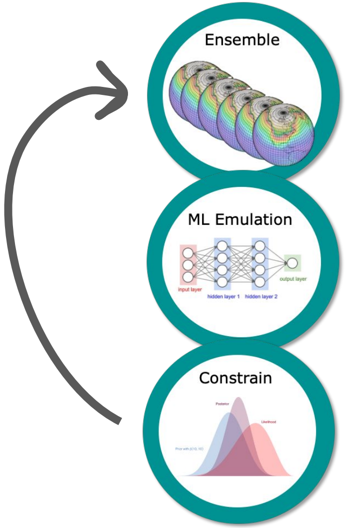
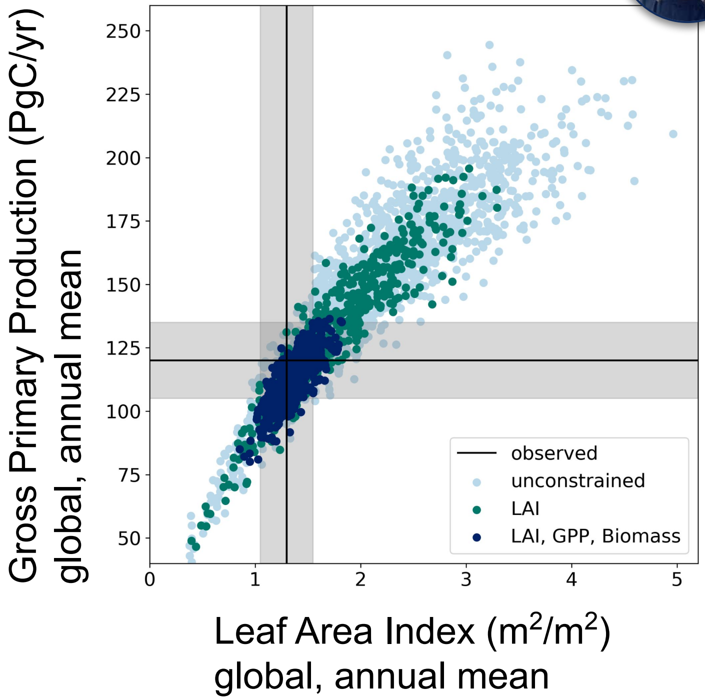


Generate a perturbed parameter ensemble
- Pick parameters of interest
- Sample them across their uncertainty ranges

Train machine learning emulator
- Emulate a dense sample

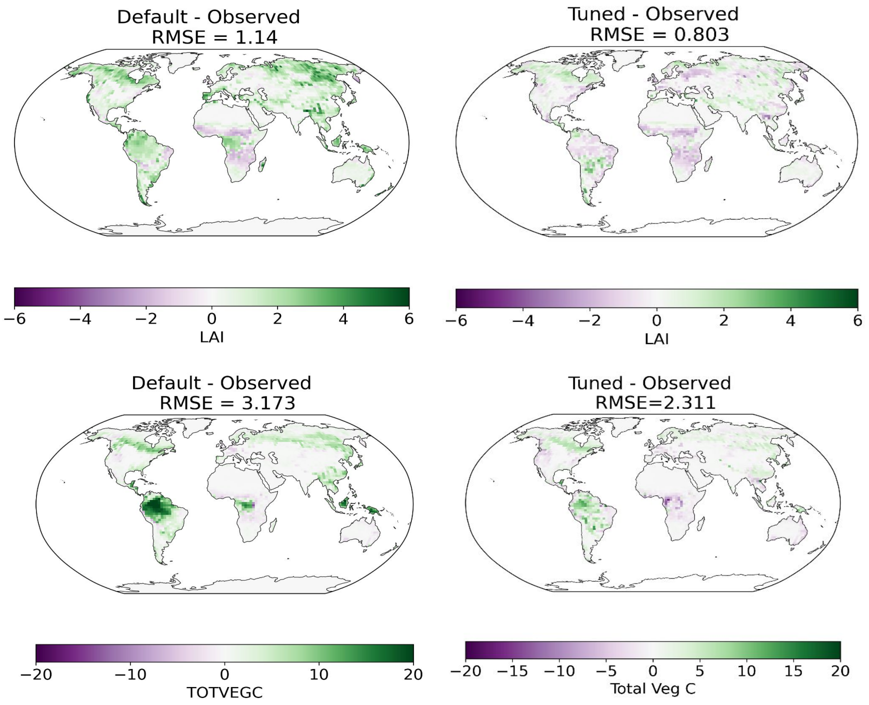
Rule out implausible parameter sets
- Can do history matching in “waves”



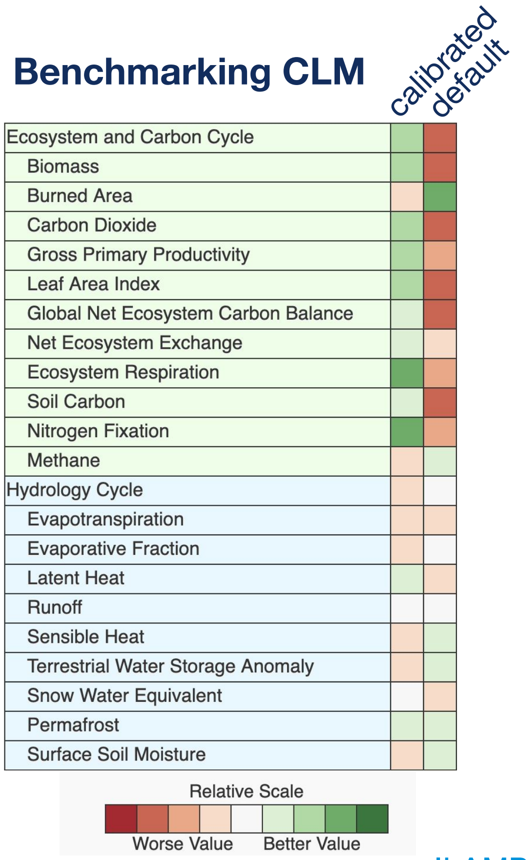
Hawkins et al. *in prep*

Calibrating CLM6 for CESM3

Default Calibrated



Benchmarking CLM



ILAMB.org

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

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

Machine Learning with CESM: Emulation

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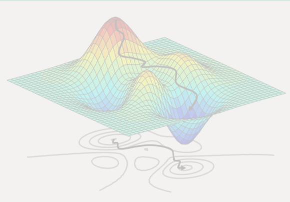

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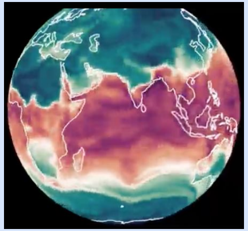

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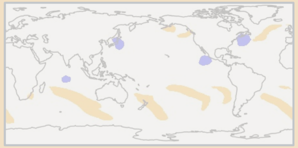

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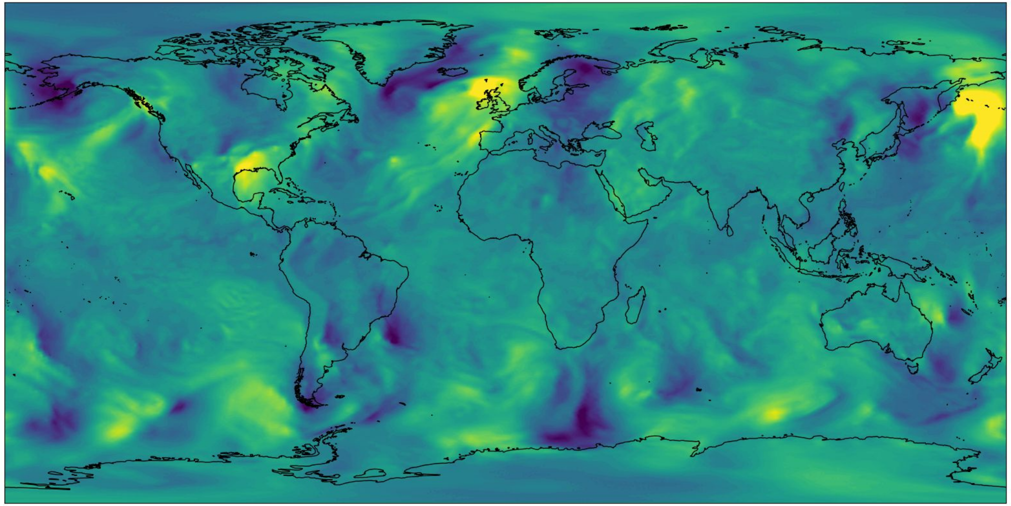
…and more!

Climate Model Emulation

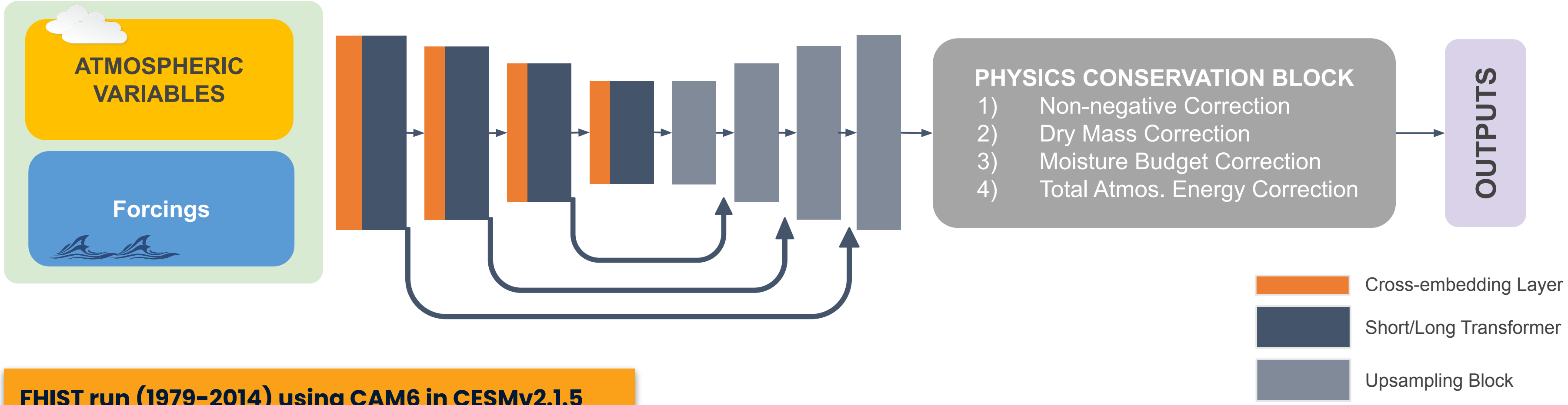
- Build on success of AI for numerical weather prediction
- Accelerate climate simulations
- Generate large projection ensembles
- Better capture internal variability and extreme events



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

CAMulator: Emulator of the Community Atmosphere Model

350x speed up over CAM6



FHIST run (1979-2014) using CAM6 in CESMv2.1.5

- O1000 lines of code
- 751,134,146 parameters
- 0.43% of GPT-3
- 2.86535 GB

Chapman et al. 2025. "CAMulator: Fast Emulation of the Community Atmosphere Model." *arXiv [Physics.Ao-Ph]*. arXiv. http://arxiv.org/abs/2504.06007.

Slide from Kirsten Mayer

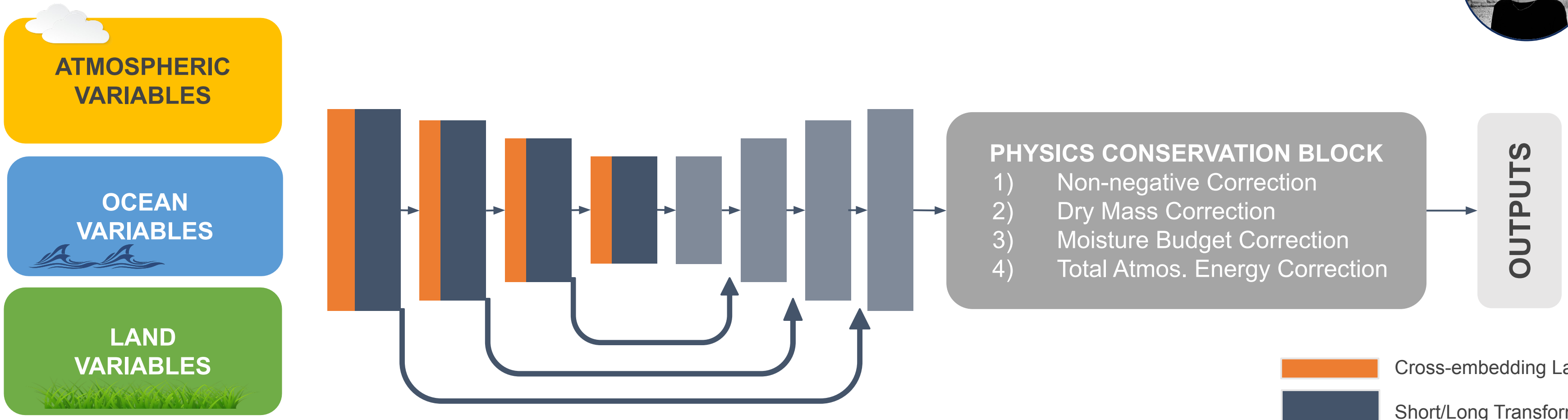
CAMulator: Emulator of the Community Atmosphere Model

See today's challenge exercise with CAMulator!

specific humidity
(lowest model level)

Chapman et al., http://arxiv.org/abs/2504.06007

subCESMulator: ML emulator for S2S Prediction



Cross-embedding Layer

Short/Long Transformer

Upsampling Block

Data: CESM2 Coupled Runs (1950-2050)
Training: 1960-2040 [80 years]
Validation: 1950-1960, 2040-2050

Mayer et al. *in prep*

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

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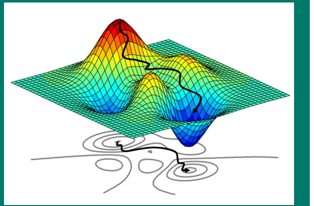

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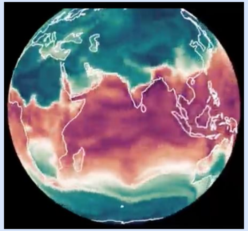

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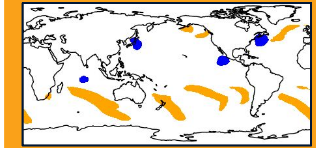

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Thanks!

Questions?

kdagon@ucar.edu

[@katiedagon](https://github.com/katiedagon)

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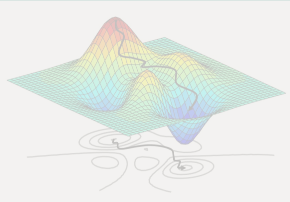
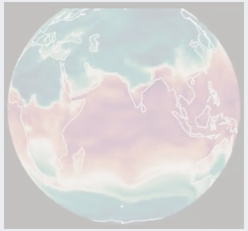
PARAMETER CALIBRATION

Calibrating CESM parameters with ML



EMULATION

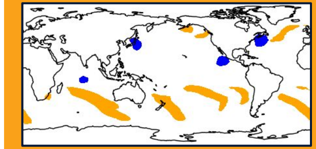
Auto-regressive emulation of CESM and component models with ML



PROCESS UNDERSTANDING

For example:

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



EMERGING AREAS

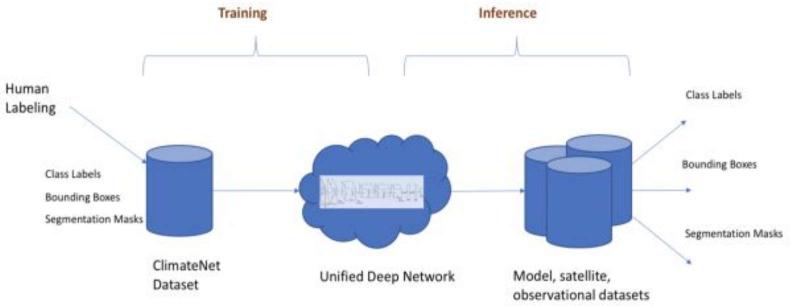
For example:

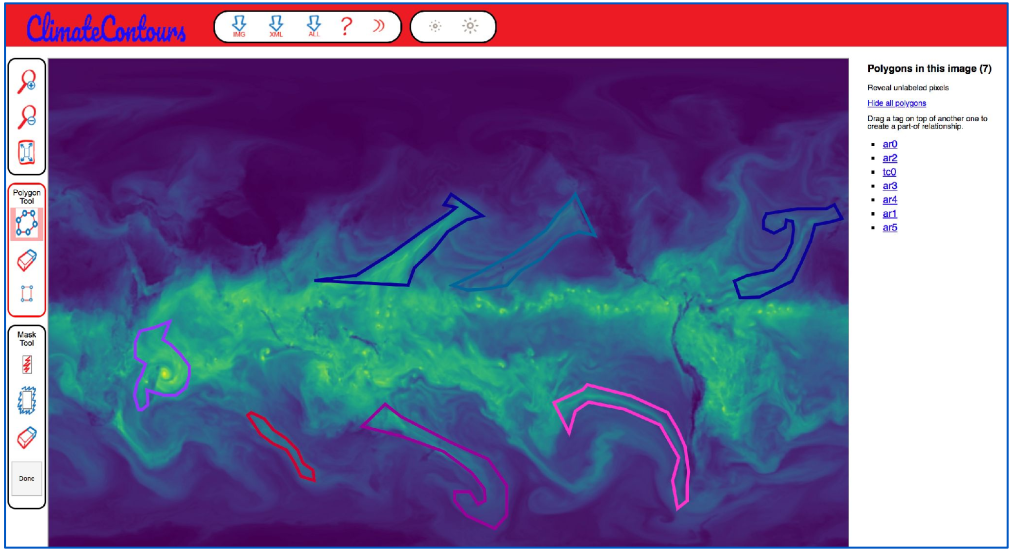
- AI-assisted code conversion
- AI dynamical downscaling
- Exploratory visualization with embeddings
- ML & data assimilation

...and more!

Machine Learning for Detection of Extremes

ClimateNet: a **community-sourced, expert-labeled** dataset for atmospheric rivers (ARs) and tropical cyclones (TCs)

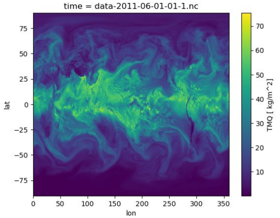




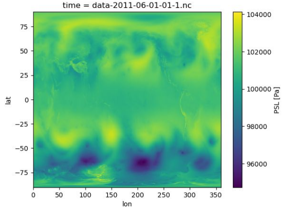
For details on ClimateNet, see:
[Prabhat et al. (2021)]

Machine Learning for Detection of Extremes

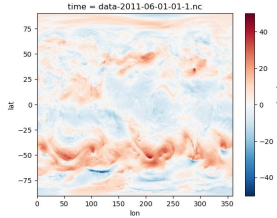
Training Input: CAM5.1 climate variables seen by expert labelers



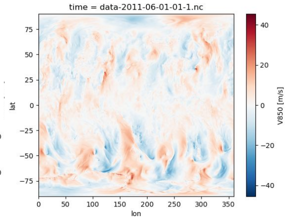
Total column water vapor



Sea level pressure

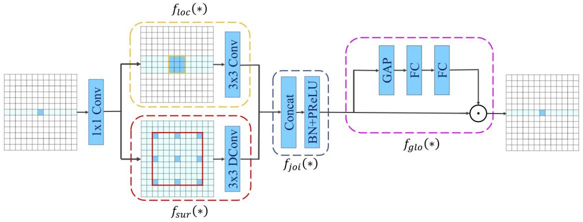


850 hPa zonal wind



850 hPa meridional wind

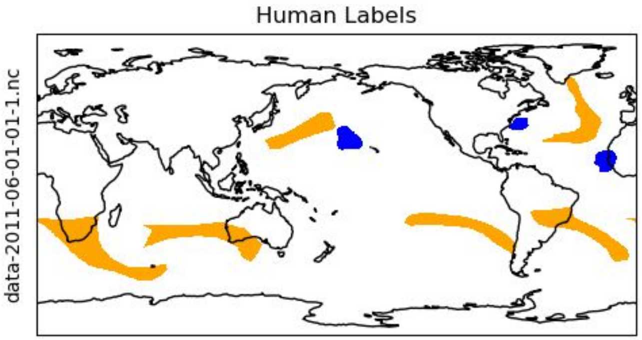
Convolutional Neural Net (CGNet)



Learning the mapping from climate variables to detected feature

For details on CGNet, see: [Kapp-Schwoerer et al. (2020)]

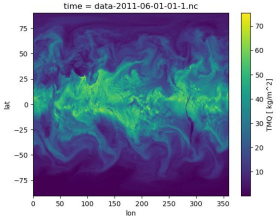
Training Output: expert labels of ARs and TCs



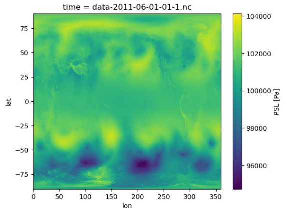
Dagon et al. *in review*

Machine Learning for Detection of Extremes

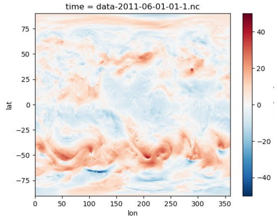
Inference Input: CESM1.3 climate variables (0.25deg, 3hrly)



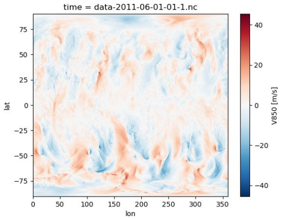
Total column water vapor



Sea level pressure

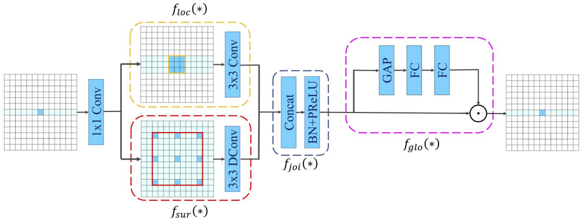


850 hPa zonal wind



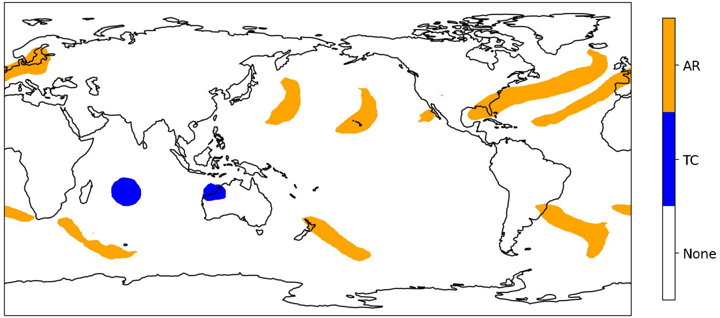
850 hPa meridional wind

Convolutional Neural Net (CGNet)



Predicting *the detected feature from climate variables*

Inference Output: predictions of ARs and TCs in CESM



Note: Prediction is per timestep; animation is from January-February 2000

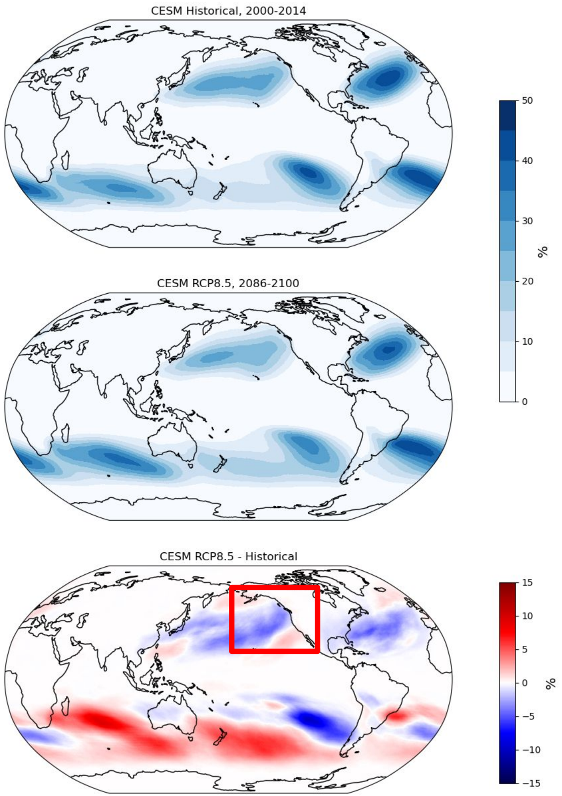
[Dagon et al. *in review*]

Future Changes in Atmospheric River Frequency

CESM historical AR frequency

CESM future (RCP8.5) AR frequency

Future - Historical



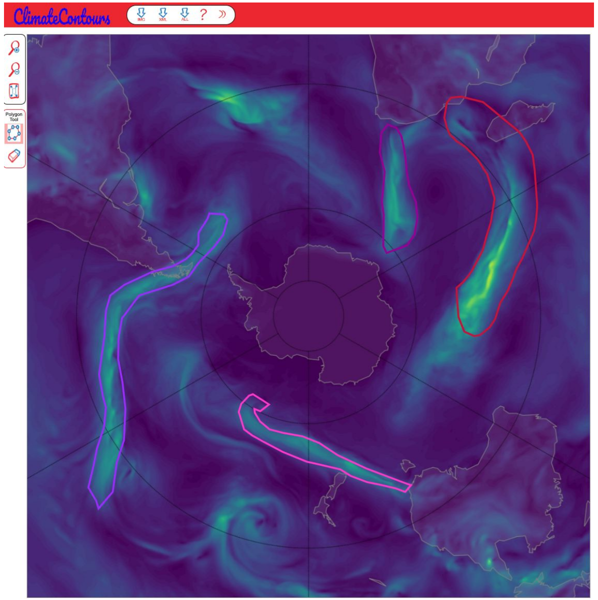
On an annual mean basis, atmospheric river (AR) frequency **largely decreases in the Northern Hemisphere** and shows mixed responses in the Southern Hemisphere.

[Dagon et al. *in review*]

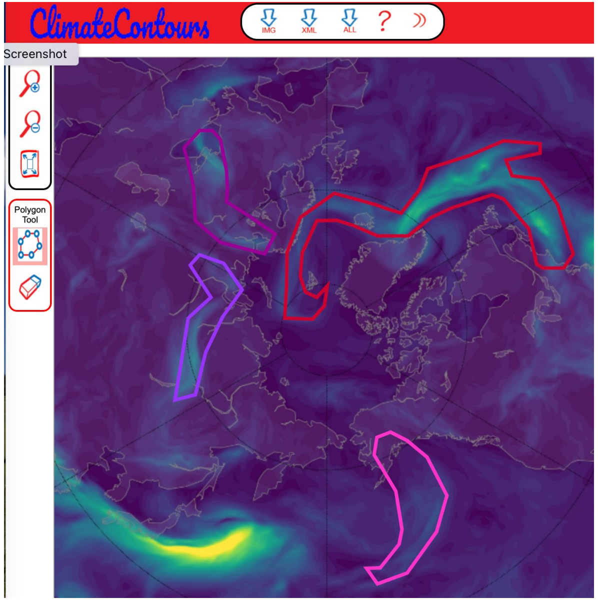
Machine Learning for Detection of Polar ARs

In development…polar AR algorithms for detecting Antarctic and Arctic atmospheric rivers:

Antarctic Labeling Tool



Arctic Labeling Tool



With: Christine Shields, Teagan King, John Truesdale, and Annette Greiner

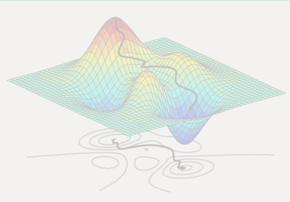
Machine Learning with CESM: Emerging Areas

HYBRID MODELING

Incorporating ML parameterizations into CESM

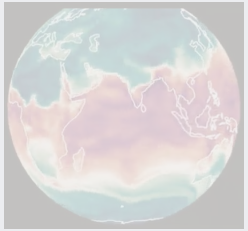
PARAMETER CALIBRATION

Calibrating CESM parameters with ML



EMULATION

Auto-regressive emulation of CESM and component models with ML



PROCESS UNDERSTANDING

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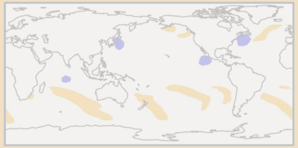


EMERGING AREAS

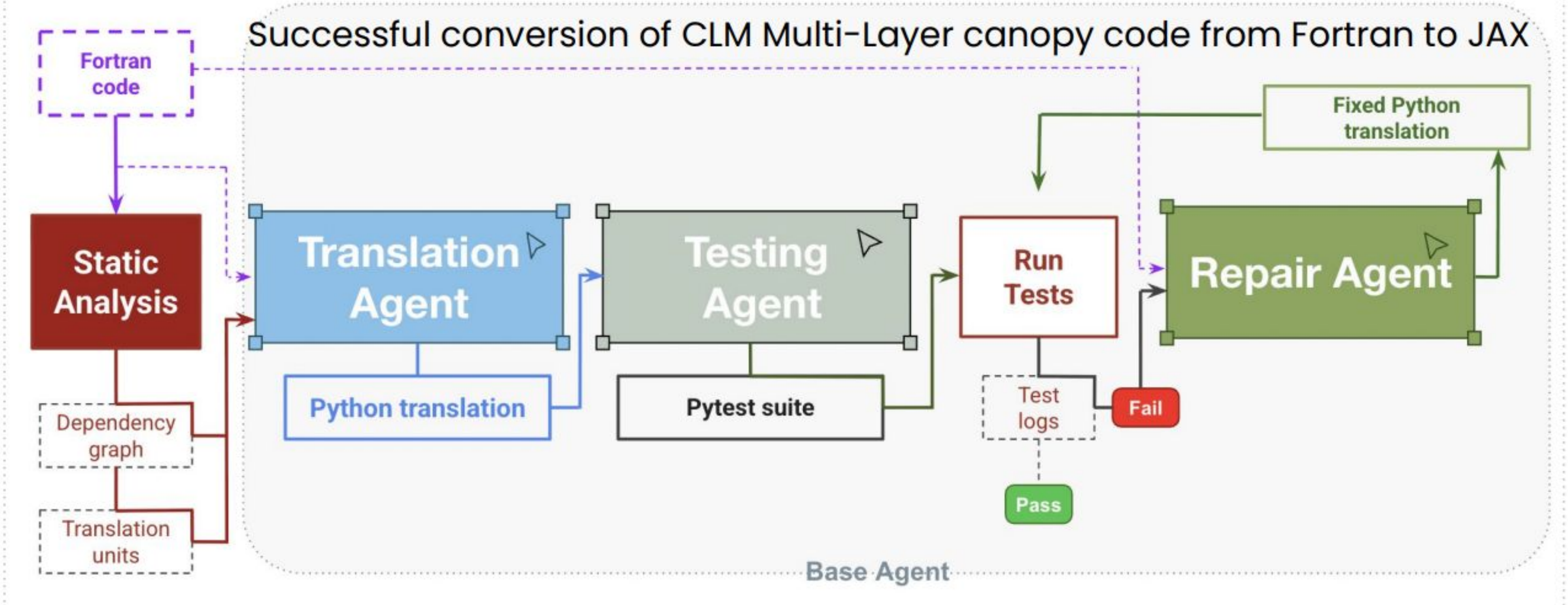
For example:

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

...and more!

Exploring AI-assisted code translation

Motivation: Differentiable, Accessible, Modern ESMs



Preprint: https://doi.org/10.48550/arXiv.2606.07681

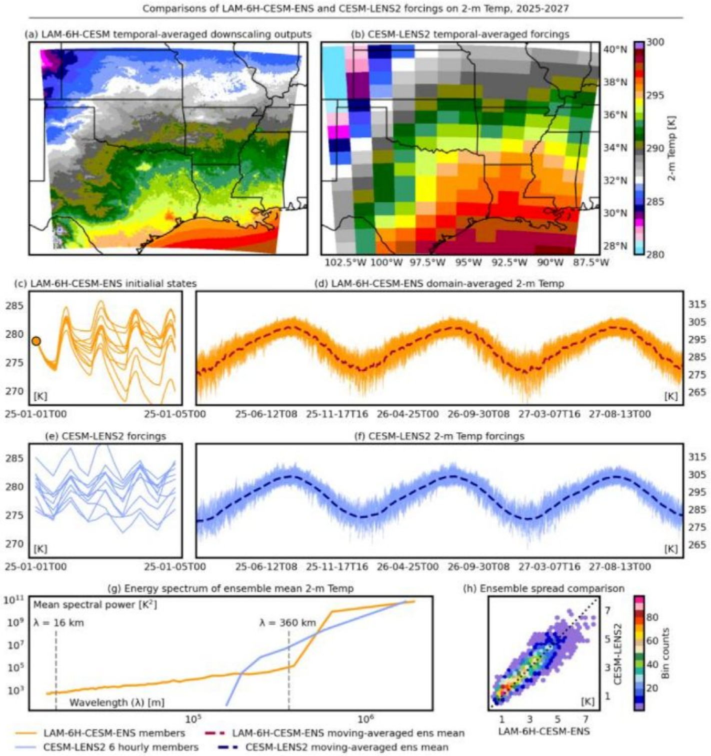
Slide from Aya Lahlou

Downscaling CESM-LENS2 10-member ensemble

2025-2027 CESM-LENS2 MOAR Downscaling performance

- 10 CESM-LENS2 members, 2025–2027 (SSP370), each member is downscaled individually.
- Members diverge from a shared start within 96 hours — member-specific trajectories
- **Spread preserved:** the 2-D spread histogram sits on the identity line; the ensemble is not collapsed
- **Mesoscale information added:** the ensemble-mean spectrum carries 10–100 km energy absent from coarse CESM (k^{-3}, $k^{-5/3}$ ranges)

→ The AI downscaling model can preserve ensemble spread + mesoscale detail from CESM ensemble.



AI-based regional downscaling for km-scale climate · Sha et al.

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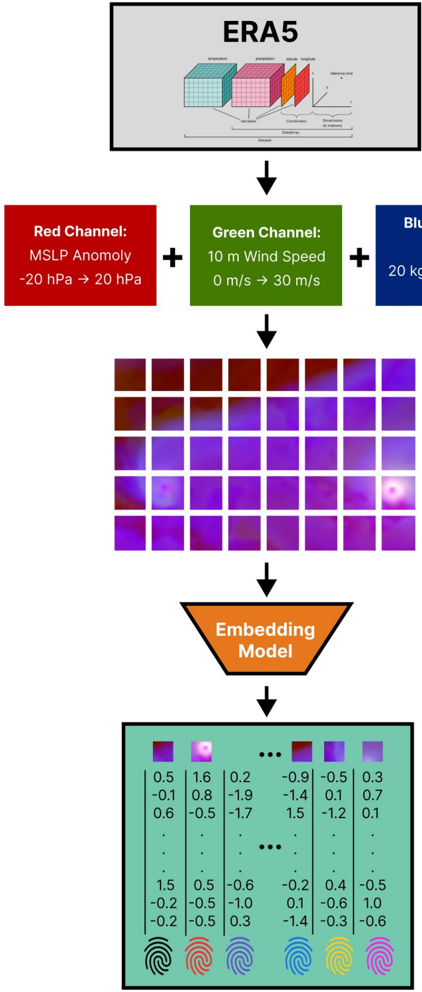
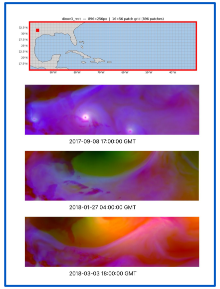
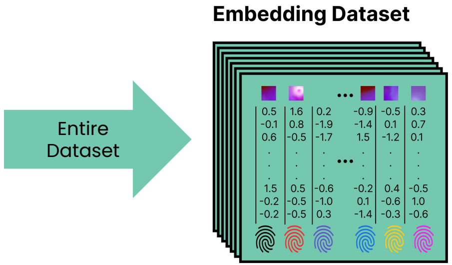
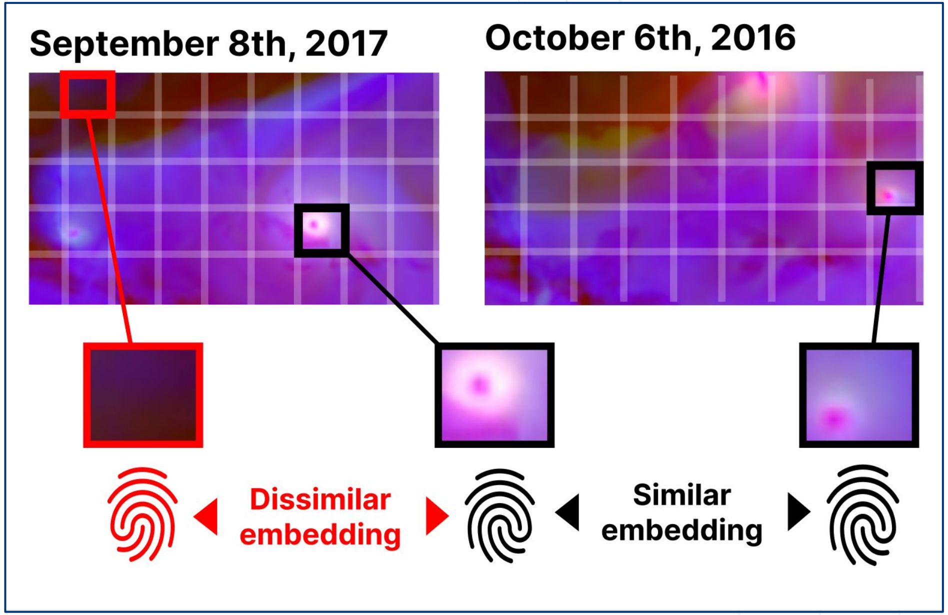
Preprint: https://arxiv.org/abs/2602.18646

Slide from Yingkai Sha









*Storage Heuristic ~ 1 additional variable

**Size of the embedding dataset is heavily dependent on the number of patches and other model parameters.*

Preprint: https://doi.org/10.48550/arXiv.2605.00972

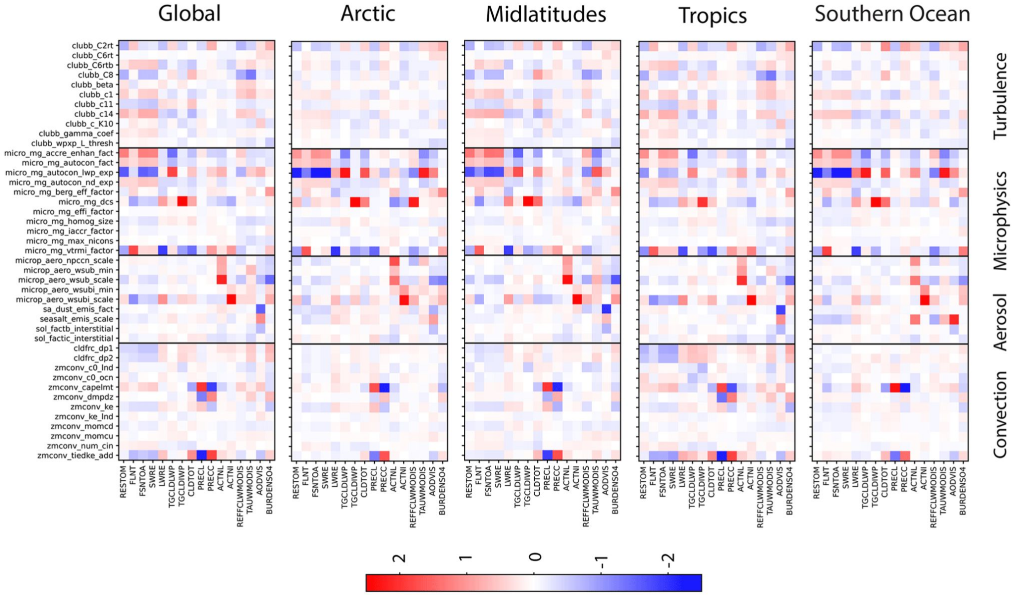
Slide from Nihanth Cherukuru

Extra Slides

CAM6 Perturbed Parameter Ensemble

Table 1. A description of the parameters that are perturbed and their ranges.

Physics scheme	Parameter name	Description	Default	Min	Max	Units
CLUBB	*clubb_C2rt*	Damping on scalar variances	1.0	0.2	2	–
	clubb_C6rt	Low skewness in C6rt skewness function	4.0	2.0	6	–
	clubb_C6rtb	High skewness in C6rt skewness function	6.0	2.0	8	–
	clubb_C6thl	Low skewness in C6thl skewness function	4.0	2.0	6	–
	clubb_C6thlb	High skewness in C6thl skewness function	6.0	2.0	8	–
	clubb_C8	Coef. no. 1 in C8 skewness equation	4.2	1.0	5	–
	clubb_beta	Set plume widths for theta_l and rt	2.4	1.6	2.5	–
	clubb_c1	Low Skewness in C1 skewness	1.0	0.4	3	–
	clubb_c11	Low Skewness in C11 skewness	0.7	0.2	0.8	–
	clubb_c14	Constant for u'^2 and v'^2 terms	2.2	0.4	3	–
	clubb_c_K10	Momentum coefficient of Kh_zm	0.5	0.2	1.2	–
	clubb_gamma_coef	Low skewness: gamma coef. skewness	0.308	0.25	0.35	–
	clubb_wpxp_L_thresh	Length-scale threshold below which extra damping is applied to C6 and C7	60	20	200	m
MG2	*micro_mg_accre_enhan_fact*	Accretion enhancing factor	1.0	0.1	10.0	–
	micro_mg_autocon_fact	Autoconversion factor	0.01	0.005	0.2	–
	micro_mg_autocon_lwp_exp	LWP exponent	2.47	2.10	3.30	–
	micro_mg_autocon_nd_exp	Autoconversion exponent	−1.1	−0.8	−2	–
	micro_mg_berg_eff_factor	Bergeron efficiency factor	1.0	0.1	1.0	–
	micro_mg_dcs	Autoconversion size threshold ice–snow	500×10^{-6}	50×10^{-6}	1000×10^{-6}	m
	micro_mg_effi_factor	Scale effective radius for optics calculation	1.0	0.1	2.0	–
	micro_mg_homog_size	Homogeneous freezing ice particle size	25×10^{-6}	10×10^{-6}	200×10^{-6}	m
	micro_mg_iaccr_factor	Scaling ice and snow accretion	1.0	0.2	1.0	–
	micro_mg_max_nicons	Maximum allowed ice number concentration	100×10^{6}	1×10^{5}	10000×10^{6}	no. kg^{-1}
	micro_mg_vtrmi_factor	Ice fall speed scaling	1.0	0.2	5.0	$m\,s^{-1}$
Aerosol	*microp_aero_npccn_scale*	Scale activated liquid number	1	0.33	3	–
	microp_aero_wsub_min	Min subgrid velocity for liquid activation	0.2	0	0.5	$m\,s^{-1}$
	microp_aero_wsub_scale	Subgrid velocity for liquid activation scaling	1	0.1	5	–
	microp_aero_wsubi_min	Min subgrid velocity for ice activation	0.001	0	0.2	$m\,s^{-1}$
	microp_aero_wsubi_scale	Subgrid velocity for ice activation scaling	1	0.1	5	–
	dust_emis_fact	Dust emission scaling factor	0.7	0.1	1.0	–
	seasalt_emis_scale	Sea salt emission scaling factor	1.0	0.5	2.5	–
	sol_factb_interstitial	Below-cloud scavenging of interstitial modal aerosols	0.1	0.1	1	–
	sol_factic_interstitial	In-cloud scavenging of interstitial modal aerosols	0.4	0.1	1	–
ZM	*cldfrc_dp1*	Parameter for deep convection cloud fraction	0.1	0.05	0.25	–
	cldfrc_dp2	Parameter for deep convection cloud fraction	500	100	1000	–
	zmconv_c0_lnd	Convective autoconversion over land	0.0075	0.002	0.1	m^{-1}
	zmconv_c0_ocn	Convective autoconversion over ocean	0.03	0.02	0.1	m^{-1}
	zmconv_capelmt	Triggering threshold for ZM convection	70	35	350	$J\,kg^{-1}$
	zmconv_dmpdz	Entrainment parameter	-1.0×10^{-3}	-2.0×10^{-3}	-2.0×10^{-4}	m^{-1}
	zmconv_ke	Convective evaporation efficiency	5.0×10^{-6}	1.0×10^{-6}	1.0×10^{-5}	$(kg\,m^{-2}\,s^{-1})^{0.5}\,s^{-1}$
	zmconv_ke_lnd	Convective evaporation efficiency over land	1.0×10^{-5}	1.0×10^{-6}	1.0×10^{-5}	$(kg\,m^{-2}\,s^{-1})^{0.5}\,s^{-1}$
	zmconv_momcd	Efficiency of pressure term in ZM downdraft CMT	0.7	0	1	–
	mconv_momcu	Efficiency of pressure term in ZM updraft CMT	0.7	0	1	–
	zmconv_num_cin	Allowed number of negative buoyancy crossings	1	1	5	–
	zmconv_tiedke_add	Convective parcel temperature perturbation	0.5	0	2	K



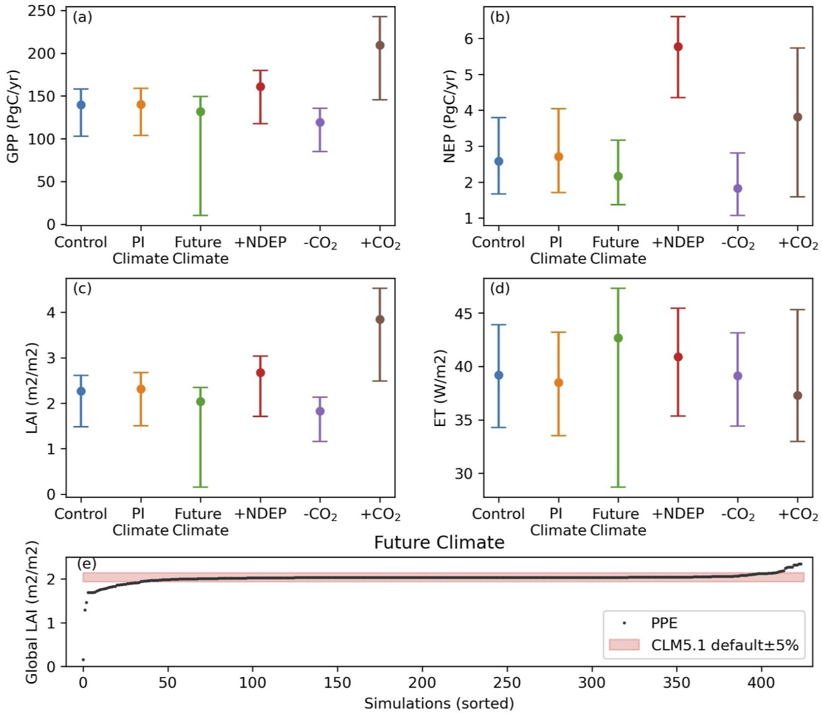
Eidhammer et al. 2024

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*

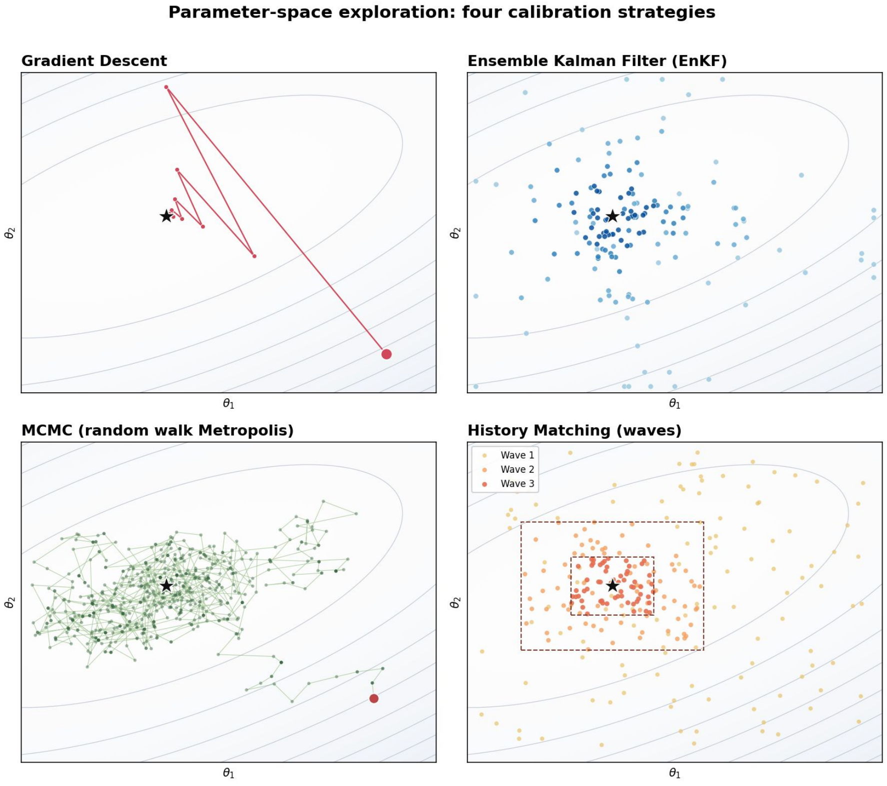
Calibration Methods Intercomparison

Gradient Descent
- Fast & efficient
- No UQ, sensitive to initialization & local minima

EnKF
- Derivative free, efficient,
- Approximates posterior & UQ
- Assumes unimodal, linear & gaussian, can collapse quickly

MCMC
- Full posterior characterization
- Handles multimodal & non-gaussian & non-linear dist.
- Expensive, sequential, sensitive to tuning.

History Matching
- Conservative, amenable to adding constraints, accounts for structural discrepancy, observational uncertainty & emulator uncertainty
- Multimodal & non-linear
- Inefficient, NROY is large



Slide from Linnia Hawkins

CAMulator input and output variables

Variable	Description	Units	Single Level/Levels
Prognostic Variables (Input and Output)			
U	Zonal Wind	m/s	32 levels
V	Meridional Wind	m/s	32 levels
T	Temperature	K	32 levels
Qtot	Specific Total Water	kg/kg	32 levels
PS	Surface Pressure	Pa	Single Level
TREFHT	Near-Surface Air Temperature	K	Single Level
Dynamic Forcing Variables (Input Only)			
SOLIN	Incoming Solar Radiation	J/m^2	Single Level
SST	Sea Surface Temperature	K	Single Level
Static Forcing Variables (Input Only)			
Surface Geop.	Normalized Surface Height	m^2/s^2	Single Level
Land-Sea Mask	Land Mask × Cosine Latitude	unitless	Single Level

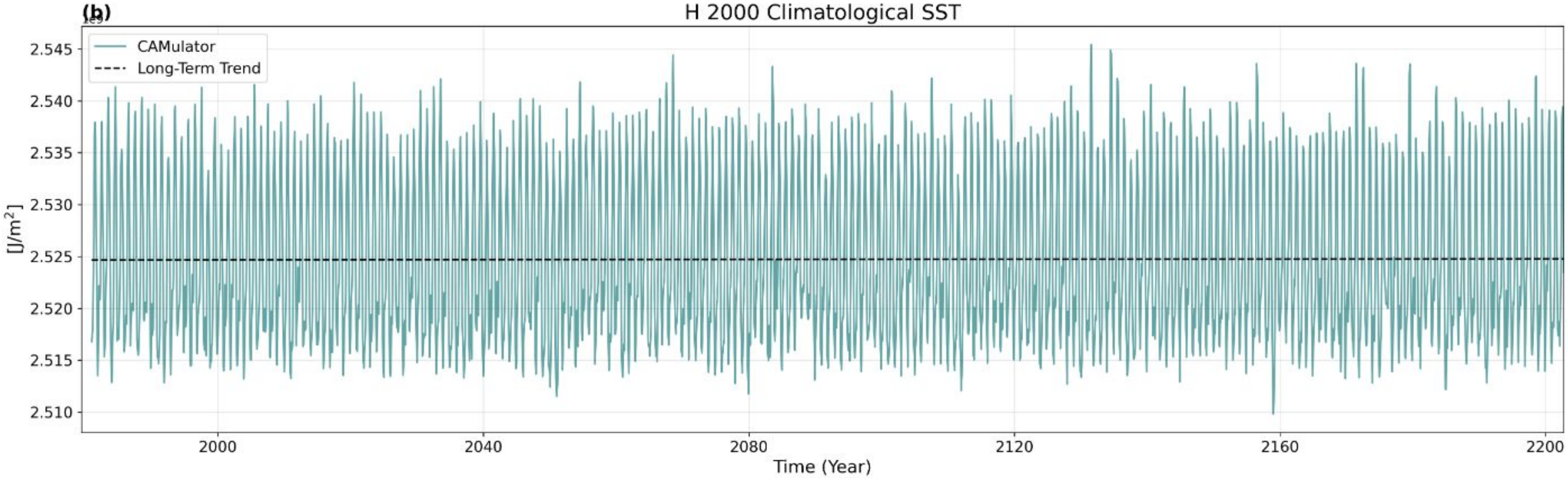
Variable	Description	Units	Single Level/Levels
Prognostic Variables (Input and Output)			
U	Zonal Wind	m/s	32 levels
V	Meridional Wind	m/s	32 levels
T	Temperature	K	32 levels
Qtot	Specific Total Water	kg/kg	32 levels
PS	Surface Pressure	Pa	Single Level
TREFHT	Near-Surface Air Temperature	K	Single Level
Diagnostic Variables (Output Only)			
PRECT	Precipitation Rate	m	Single Level
CLDTOT	Total Cloud Cover	fraction	Single Level
CLDHGH	High Cloud Cover	fraction	Single Level
CLDLOW	Low Cloud Cover	fraction	Single Level
CLDMED	Medium Cloud Cover	fraction	Single Level
TAUX	Zonal Wind Stress	N/m^2	Single Level
TAUY	Meridional Wind Stress	N/m^2	Single Level
U10	10m Wind Speed	m/s	Single Level
QFLX	Surface Moisture Flux	m	Single Level
FSNS	Net Solar Flux at Surface	J/m^2	Single Level
FLNS	Net Longwave Flux at Surface	J/m^2	Single Level
FSNT	Net Solar Flux at TOA	J/m^2	Single Level
FLNT	Net Longwave Flux at TOA	J/m^2	Single Level
SHFLX	Sensible Heat Flux	J/m^2	Single Level
LHFLX	Latent Heat Flux	J/m^2	Single Level

Prognostic: input & output
Forcing Variables: input
Diagnostic: output

Chapman et al., http://arxiv.org/abs/2504.06007

CAMulator performance: long run

What if we rolled it out for more than 200 years?

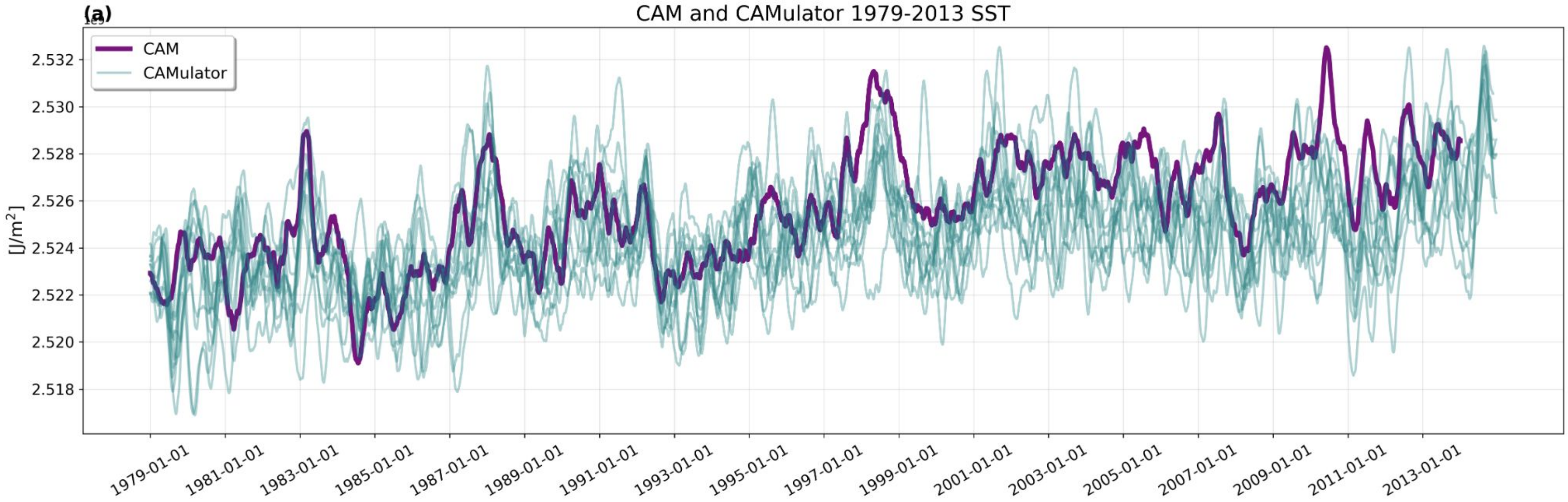


Column-integrated heat content in CAMulator to fixed year-2000 climatological SSTs

Chapman et al., http://arxiv.org/abs/2504.06007

CAMulator performance: response to forcing

What if we force it with observed SSTs?



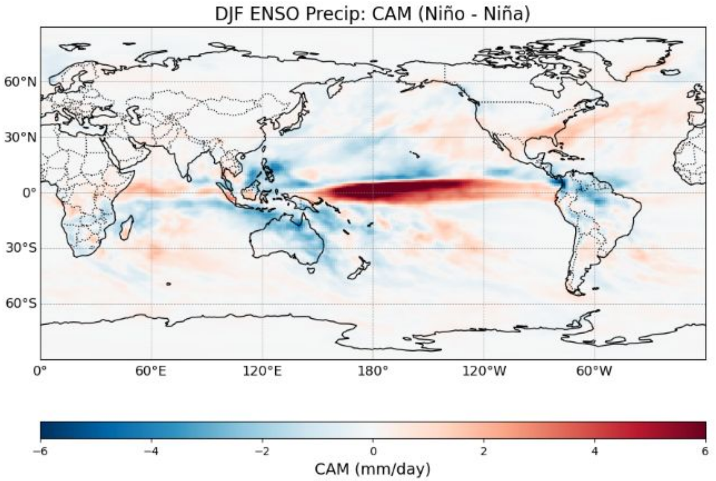
A 12-member CAMulator ensemble (teal) is compared to the CAM6 simulation (purple) using observed SSTs from 1979–2014. CAMulator successfully captures the long-term warming trend and interannual variability.

Chapman et al., http://arxiv.org/abs/2504.06007

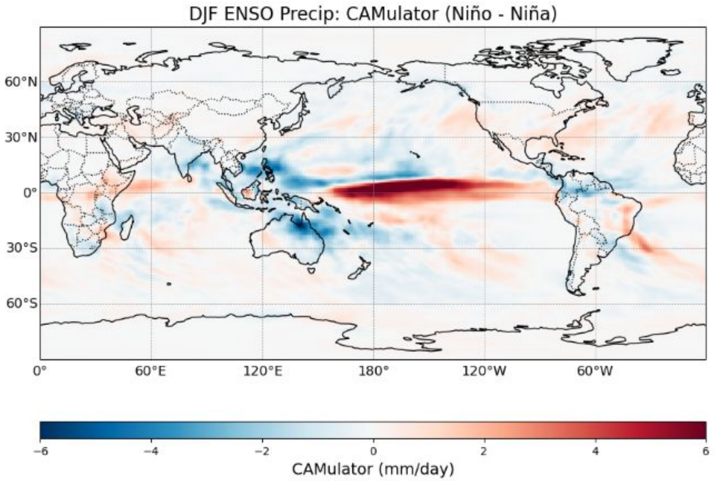
CAMulator performance: ENSO precipitation

ENSO Precip Response (8 strongest Nino-Nina):

CAM6 DJF



CAMulator DJF

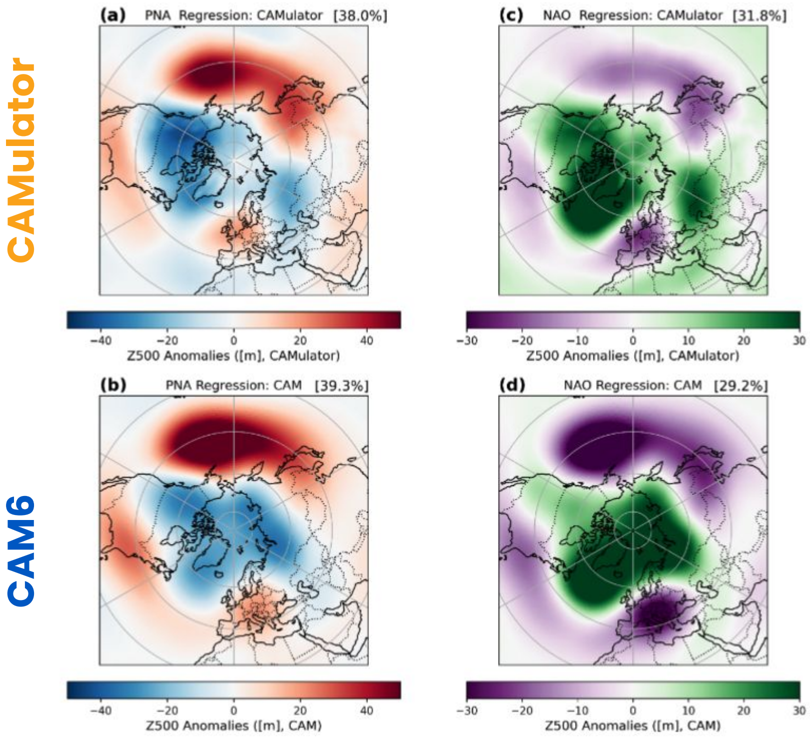


Precipitation Anomaly [mm/day]

Pattern Correlation: ~0.9

Chapman et al., http://arxiv.org/abs/2504.06007

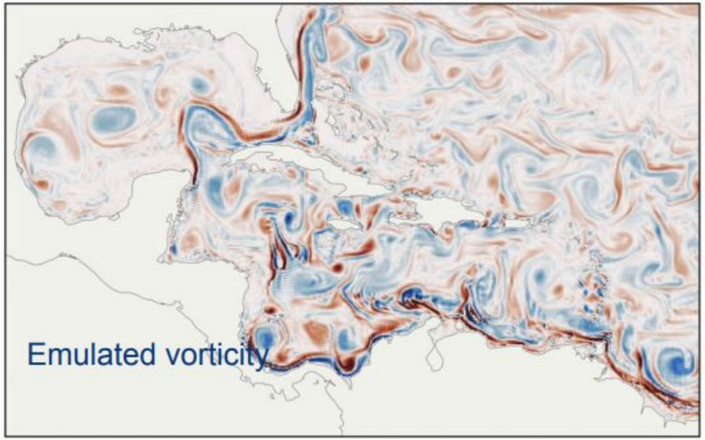
CAMulator performance: Modes of Variability

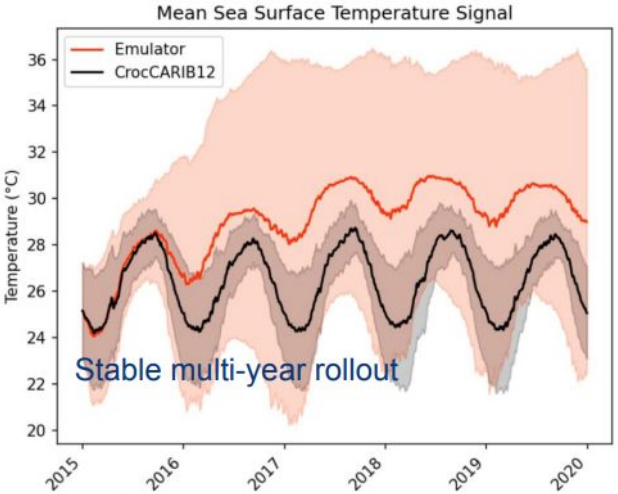


MOVs fall within the spread of CAM

Chapman et al., http://arxiv.org/abs/2504.06007

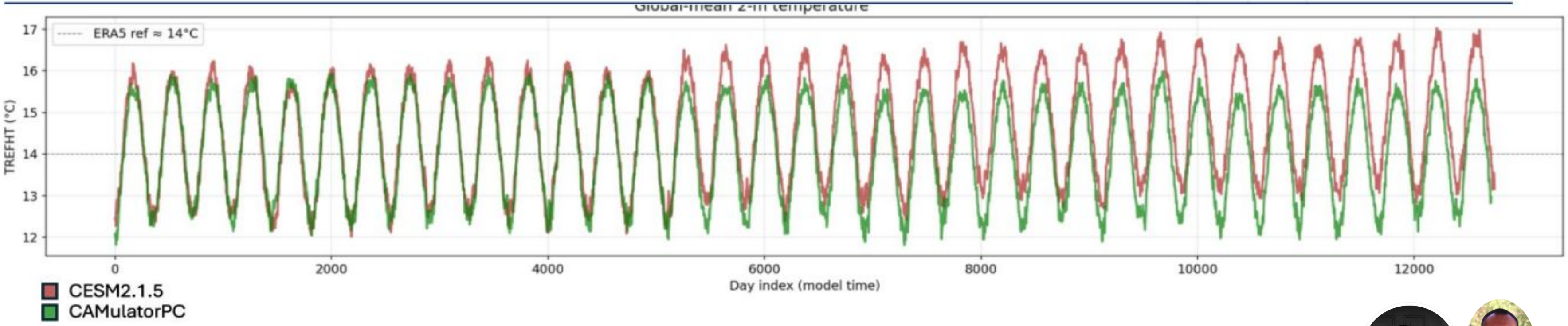
Emulation of regional MOM6 with CREDIT (MOMulator)



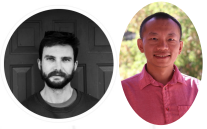


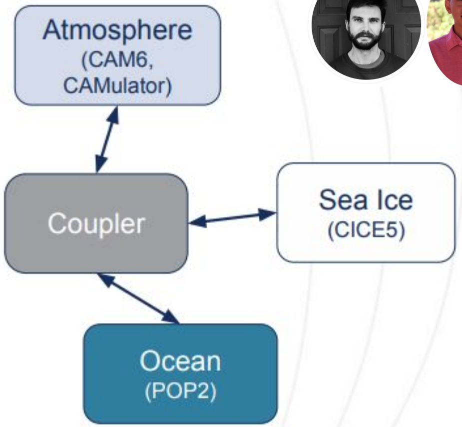
Aidan Janney (now NCAR Scientist I) CU senior thesis: Emulating 1/12 MOM6 in the Caribbean (Seijo-Ellis et al 2024) using the CREDIT platform

Goal: Flexibly coupled AiCESM (CESMulator)



- **Maintains long-term stability after coupling**
  - Minor drift then settling after ~100-year spin-up over long simulations
- **Seasonal cycle remains intact**
  - Correct amplitude and phase preserved
  - No degradation of large-scale energy balance
- **Mean-state biases remain controlled**
  - Small, consistent offset relative to host model (CESM2.1.5 1979 -2015 shown)
- **Coupling does not destabilize emulator**
  - Atmosphere–surface interactions remain stable





Will Chapman, Yuanpu Li (University of Colorado)