



February 03, 2026

Extending CAMulator for Subseasonal Prediction

Simulations, Applications, and Performance

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Scientist IV; CGD ESP

Charlie Becker, Katie Dagon, John Schreck, David John Gagne, Will Chapman, Sasha Glanville, Judith Berner, Abby Jaye, Negin Sobhani

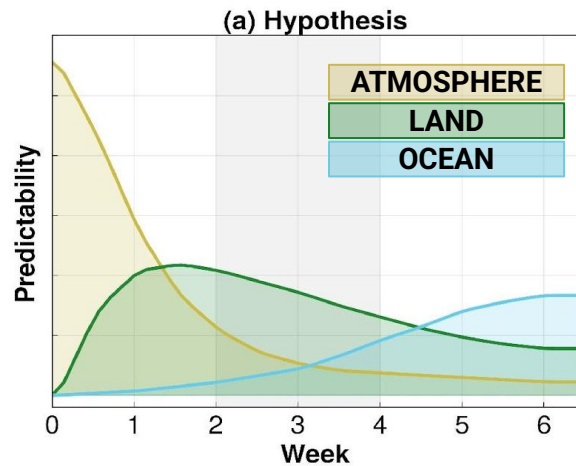
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catalyst

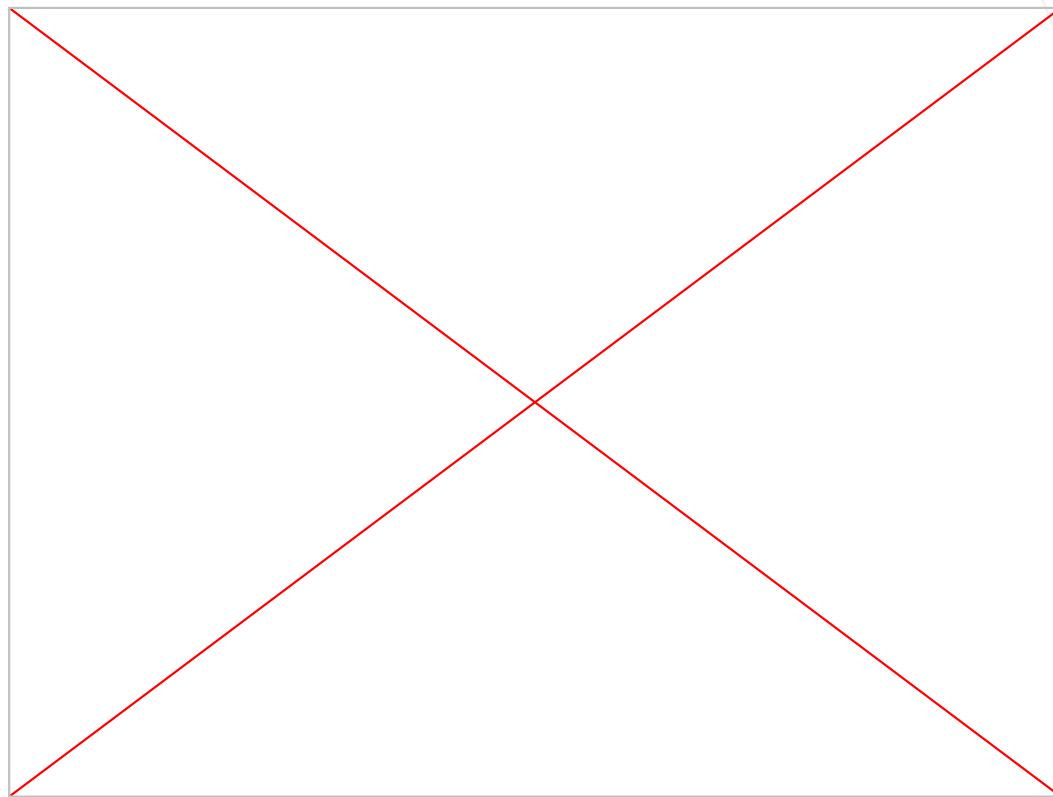
Subseasonal Timescales: ~2 weeks – 2 months



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CAMulator: Emulator of the Community Atmosphere Model

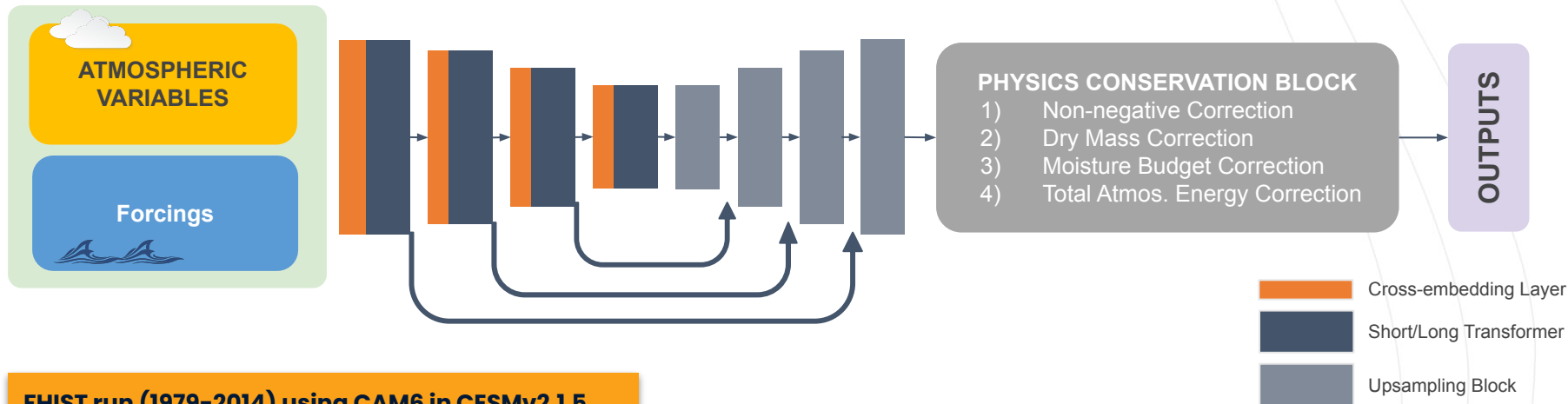


specific humidity
(lowest model level)

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

CAMulator: Emulator of the Community Atmosphere Model



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
Otot	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



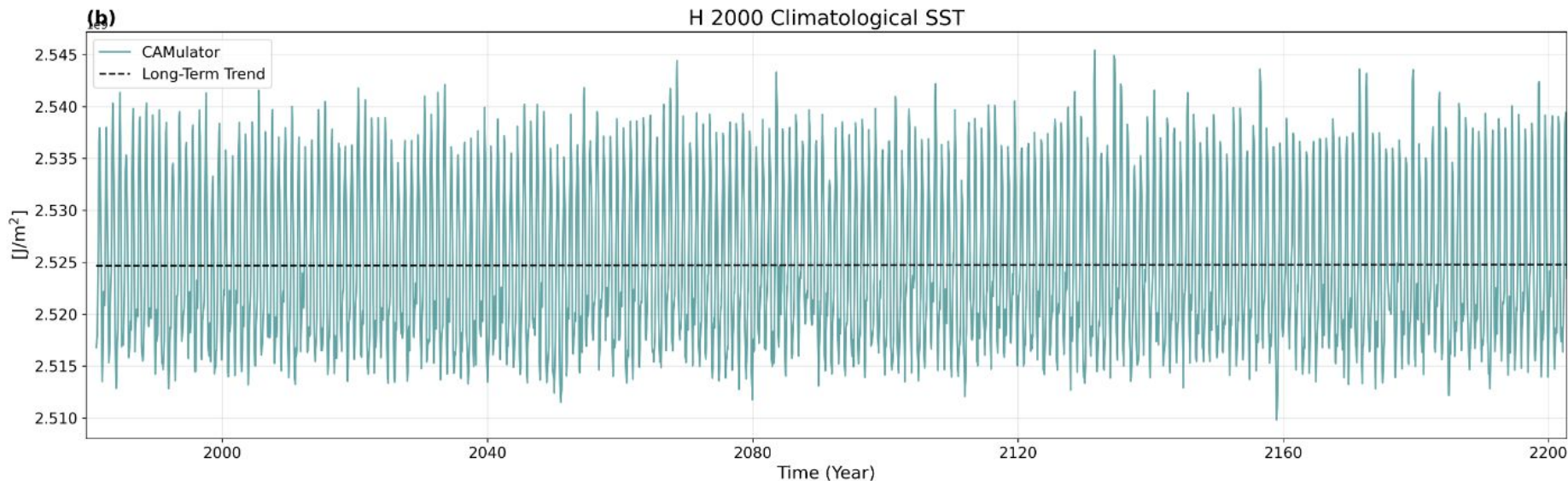
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PS	Surface Pressure	Pa	Single Level
TREFHT	Near-Surface Air Temperature	K	Single Level
Diagnostic Variables (Output Only)			
PRECT	Precipitation Rate	m	Single Level
CLDTOT	Total Cloud Cover	fraction	Single Level
CLDHGH	High Cloud Cover	fraction	Single 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

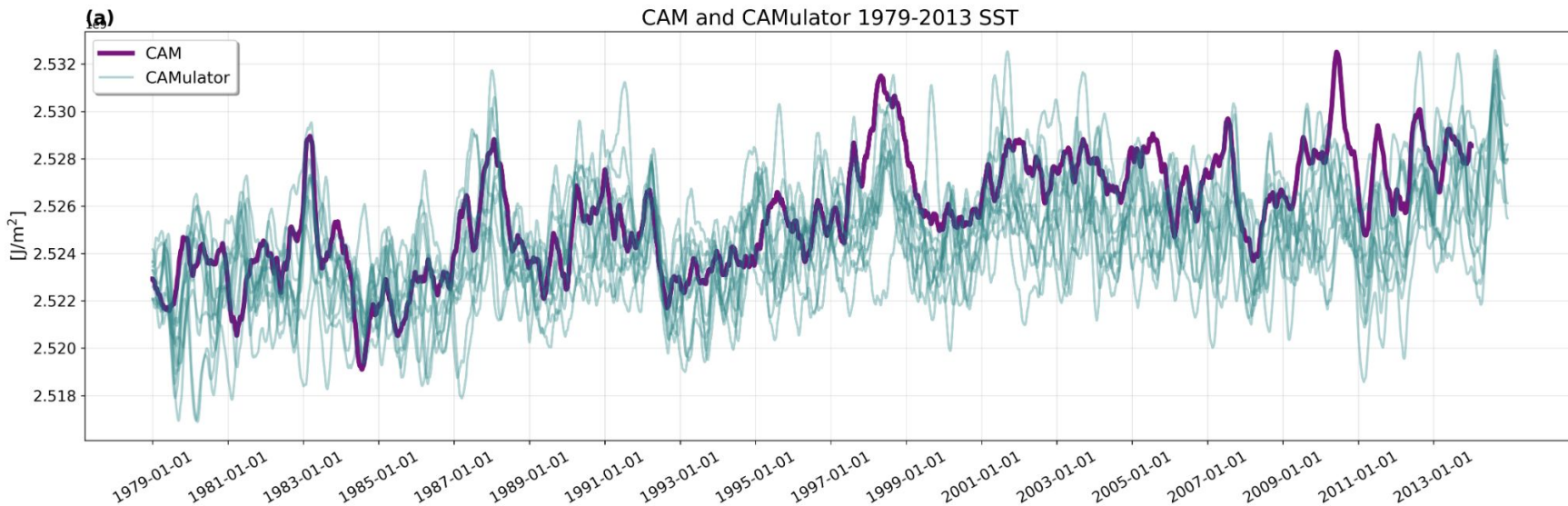
Diagnostic: output

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



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

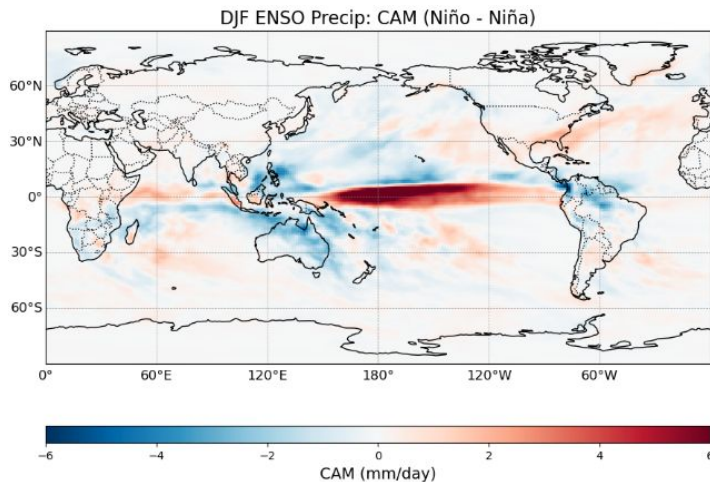
What if we force it with observed SSTs?



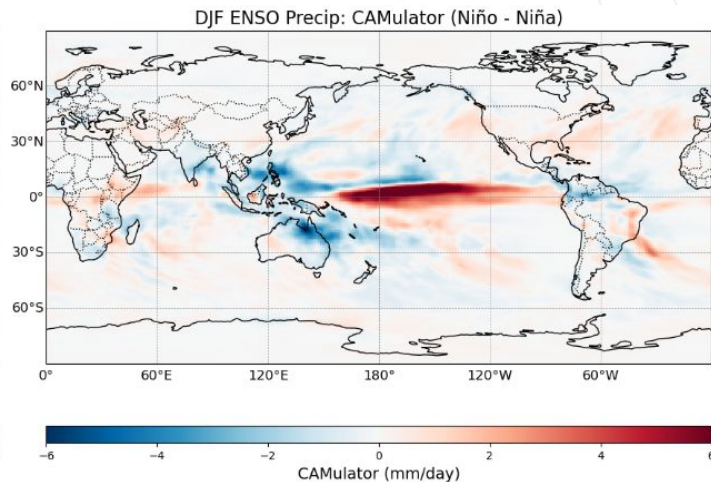
A 12-member CAMulator ensemble (teal) is compared to the CAM6 simulation (purple) using observed SSTs from 1979–2014. CAMulator successfully captures the long-term warming trend and interannual variability.

ENSO Precip Response (8 strongest Nino-Nina):

CAM6 DJF



CAMulator DJF



Precipitation Anomaly [mm/day]

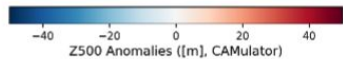
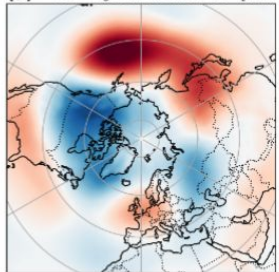
Pattern Correlation: ~0.9

CAMulator: Emulator of the Community Atmosphere Model

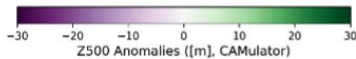
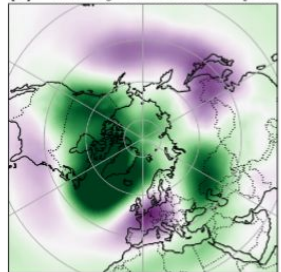


CAMulator

(a) PNA Regression: CAMulator [38.0%]

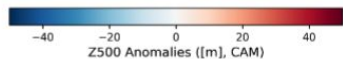
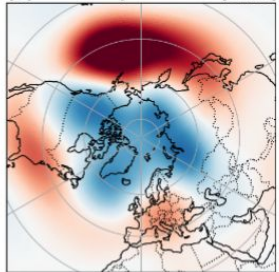


(c) NAO Regression: CAMulator [31.8%]

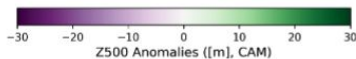
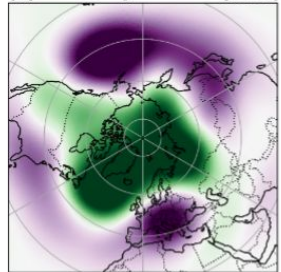


CAM6

(b) PNA Regression: CAM [39.3%]



(d) NAO Regression: CAM [29.2%]





CAMulator v1
Training Data-AMIP

A green rectangular box with a white outline and a folded top-right corner, containing the word "UPDATE" in bold black capital letters.

UPDATE

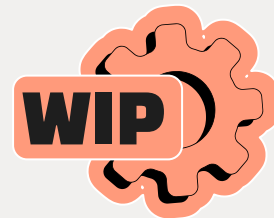
CAMulator v2
Training Data-Coupled



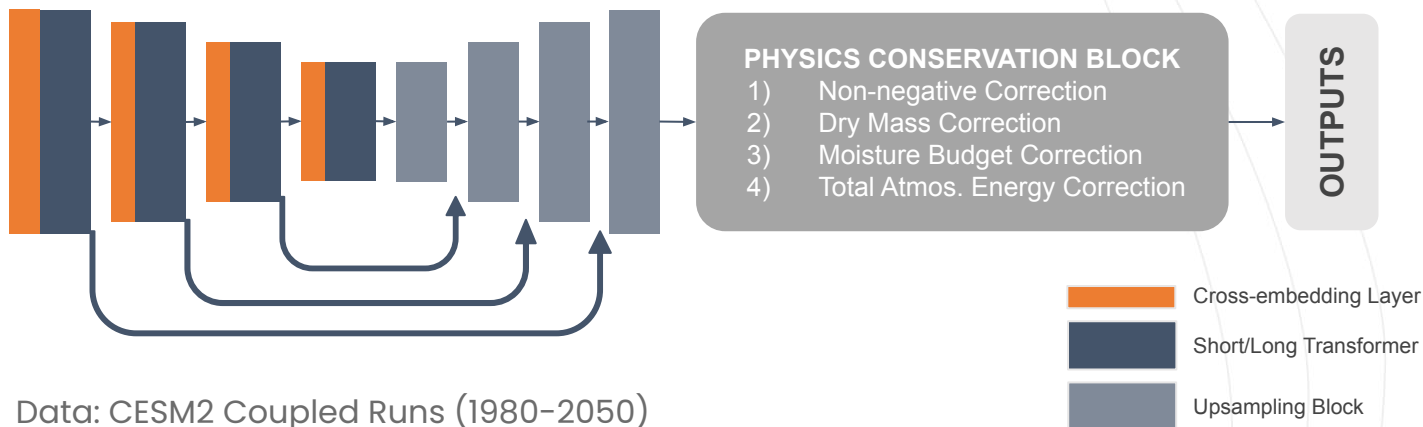
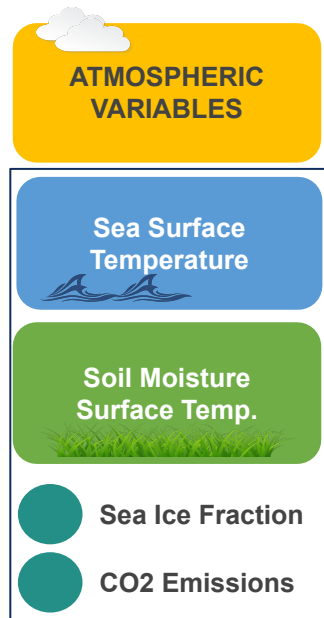
CAMulator v1
Training Data-AMIP

UPDATE

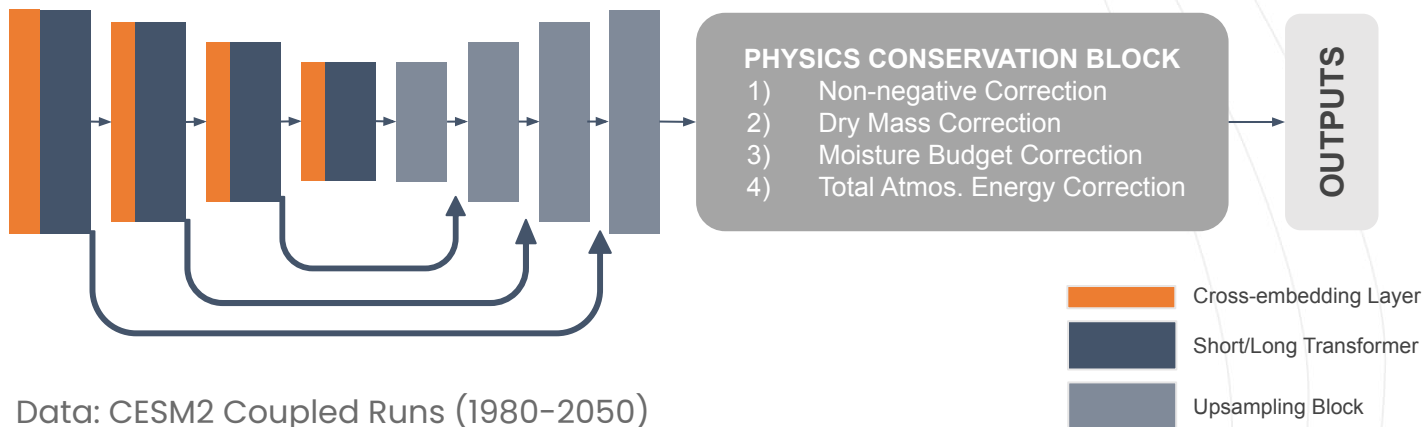
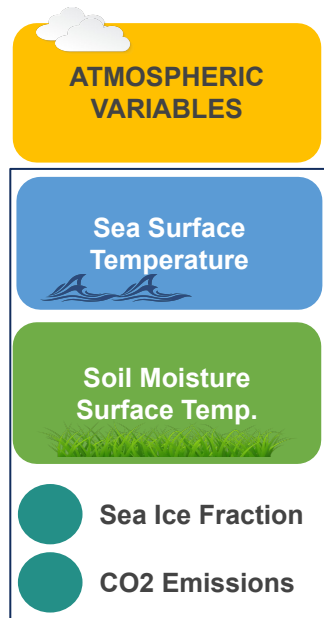
CAMulator v2
Training Data-Coupled



subCESMulator
+ ocean & land



Data: CESM2 Coupled Runs (1980–2050)
Training: 1980–2024
Validation: 2025–2030



Data: CESM2 Coupled Runs (1980–2050)
Training: 1980–2024
Validation: 2025–2030

Modified subCESMulator

Data: CESM2-LE

Training: 1990–2025 x 5 members = 175 years
(typical S2S models train on 1979–2025 = 46 years)

+ more land & ocean variables

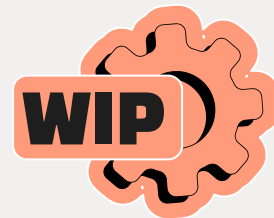


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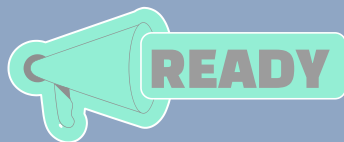
UPDATE

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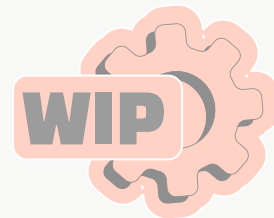
...Mulator: ML Emulators to date



CAMulator v1
Training Data-AMIP

UPDATE

CAMulator v2
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subCESMulator
+ ocean & land

AI Weather Quest Submission

Kirsten J. Mayer, Katherine Dagon, William E. Chapman, Charlie Becker,
John Schreck, David John Gagne, Judith Berner, Abby Jaye, Sasha Glanville

Can we use a AI model trained on CESM for subseasonal forecasting?

AI Weather Quest

By  ECMWF

The AI Weather Quest, organised by the European Centre for Medium-Range Weather Forecasts (ECMWF), is an ambitious international competition designed to harness artificial intelligence (AI) and machine learning (ML) in advancing sub-seasonal weather forecasting. With **35+ international teams**, **170+ participants**, and **60+ AI/ML models**, it is already setting a new benchmark for sub-seasonal prediction. **See how they perform and add your forecasts to the challenge!**

Loegel et al. 2025

Participants provide **weekly, global forecasts** at a 1.5 degree resolution of **quintile probabilities** for weekly-mean (Days 19–25 and Days 26–32):

- **Temperature**
- **Precipitation**
- **Sea level pressure**

Evaluated against initial **ERA5** release data using ranked probability skill score (**RPSS**)



INITIALIZATION

We initialize with 11 perturbations of each 31 member of **GEFS initializations (341 members)**

→ Perturbation method based on CESM S2S hindcast method (see Section 2.b of Richter et al. 2022)

DYNAMICAL FORCING

SST and ICEFRAC are forcing variables in CAMulator, so we **persist their initial conditions** throughout forecast

QUINTILES

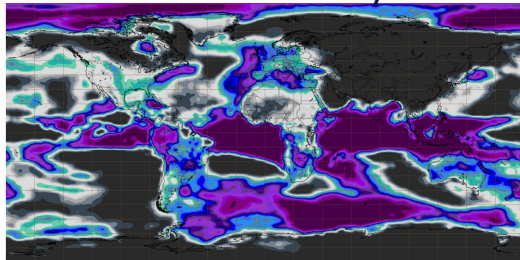
CAMulator is trained on coupled runs, so we **calculate quintiles based on CESM training data (2000-2025)**

Takes ~7 hrs
to submit

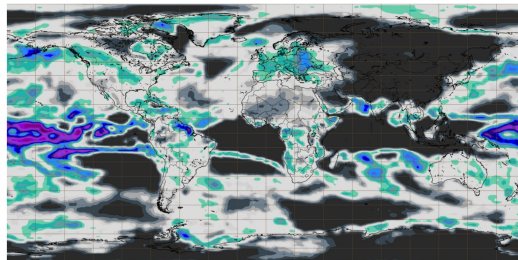
Week 3 Forecast: 02 February – 08 February 2m Temperature



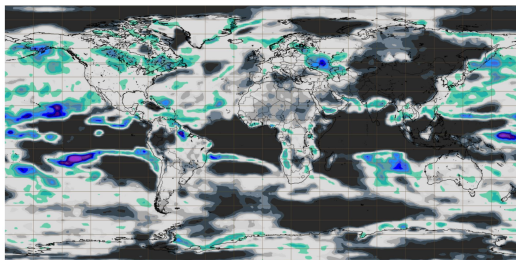
<20th: Anomalous Cold



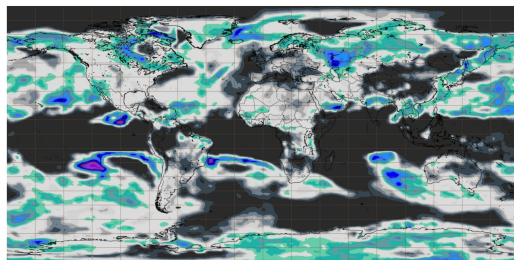
20th-40th



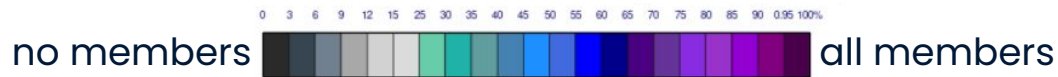
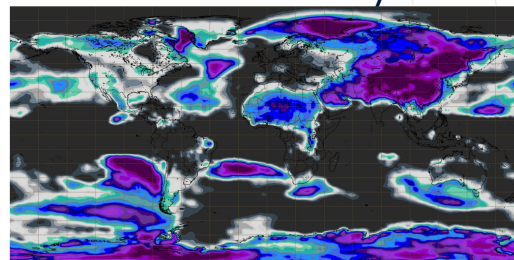
40th - 60th



60th - 80th

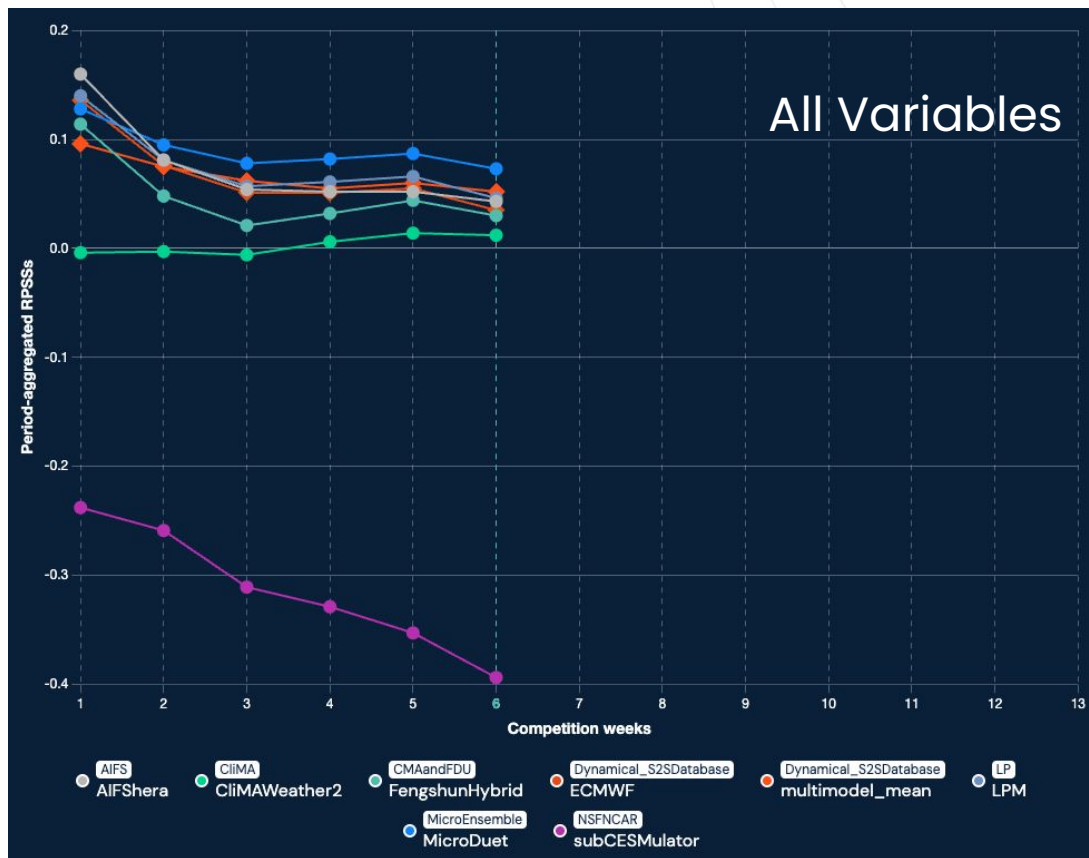


>80th: Anomalous Warm



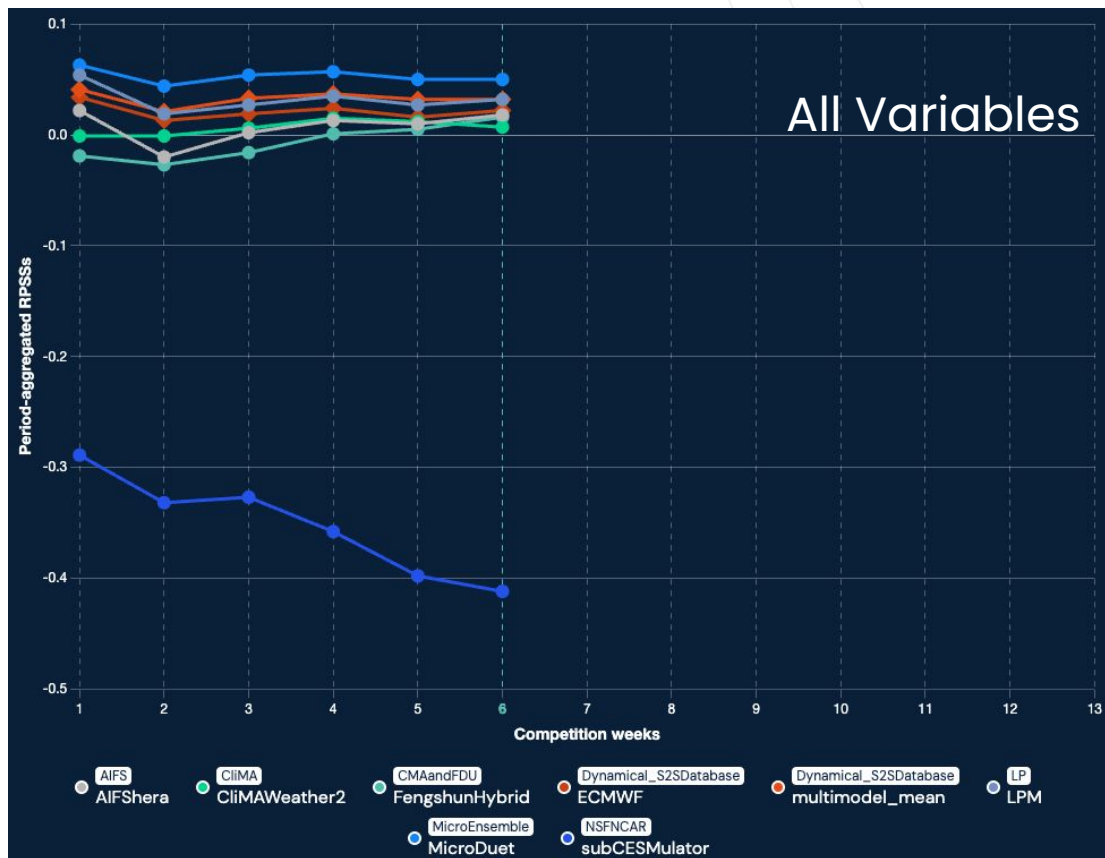
WEEK 3:

- All Variables
 - 14th out of 20 teams
 - 28th out of 36 models
- 2m Temperature
 - 20th out of 22 teams
 - 38th out of 40 models
- MSLP
 - 17th out of 20 teams
 - 34th out of 38 models
- Precipitation
 - 16th out of 21 teams
 - 33rd out of 40 models



WEEK 4:

- All Variables
 - 14th out of 20 teams
 - 29th out of 37 models
- 2m Temperature
 - 20th out of 22 teams
 - 39th out of 41 models
- MSLP
 - 17th out of 20 teams
 - 34th out of 38 models
- Precipitation
 - 16th out of 21 teams
 - 33rd out of 40 models



MODEL

Move from CAMulator to subCESMulator

ENSEMBLE GENERATION

Switch to **Stochastic Decomposition Layers** which has shown good spread-skill ratios through medium-range forecasts in WxFormer (Schreck et al. 2025)

EVALUATION

Explore skill of real-time forecasts beyond quintiles & identify areas of improvement



U.S. DEPARTMENT
of **ENERGY**
Office of Science

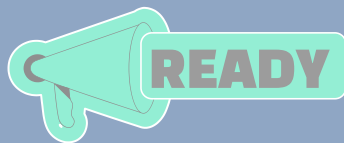


NCAR
UCAR

ML S2S Hindcasts

Kirsten J. Mayer, Charlie Becker, Sasha Glanville, John Schreck, Judith Berner, Abby Jaye, Negin Sobhani

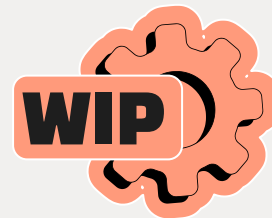
...Mulator: ML Emulators to date



CAMulator v1
Training Data-AMIP

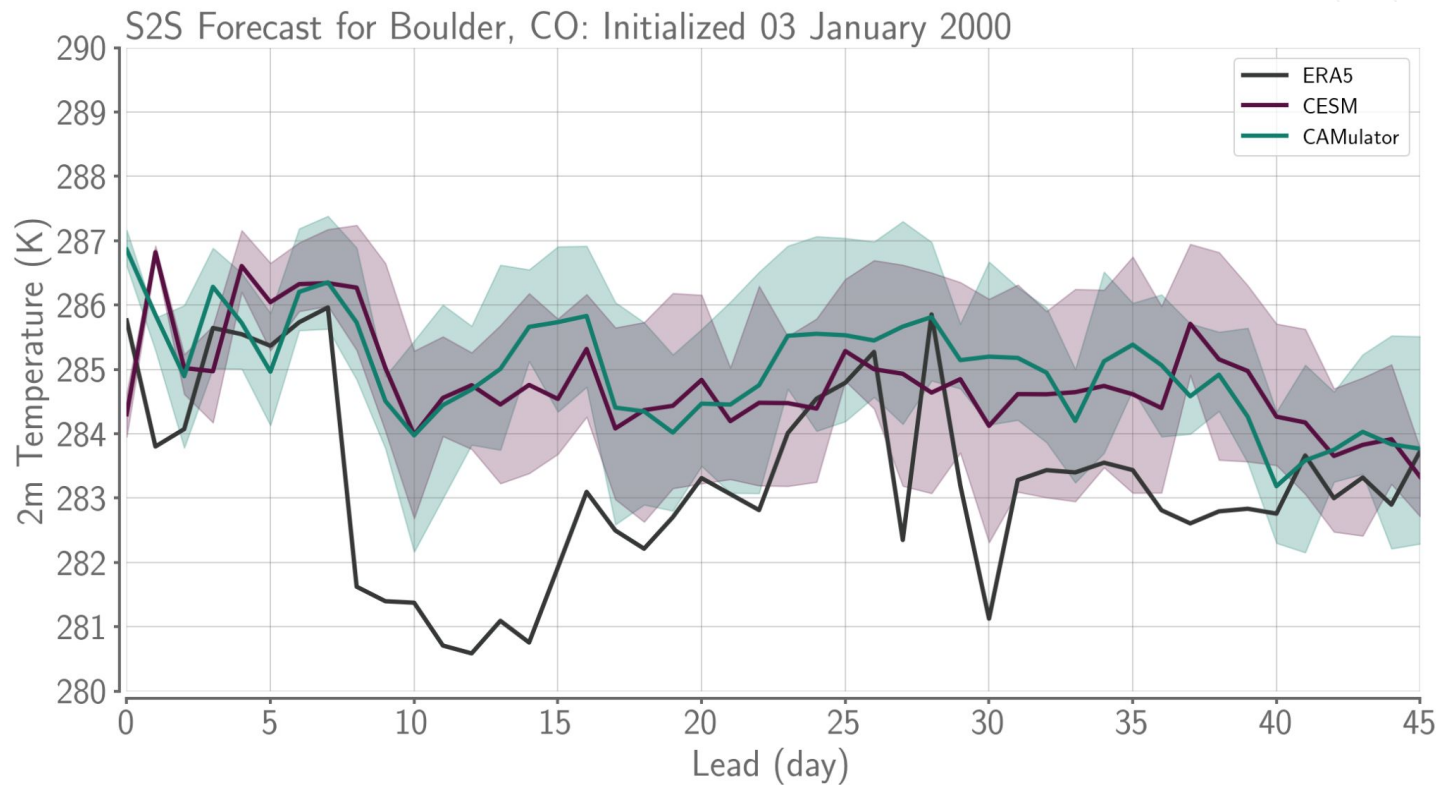
UPDATE

CAMulator v2
Training Data-Coupled



subCESMulator
+ ocean & land

- 1 CAMulator and subCESMulator
- 2 Use same initial conditions & ensemble generation as the CESM S2S Hindcasts
- 3 Explore additional ensemble generation approaches with >10 members
- 4 Run additional (and extended) initialization dates
- 5 Apply diagnostic package
- 6 Make available to the community



CAMulator Hindcasts

subCESMulator Training

One trained on CESM coupled simulation and another using the CESM2-LE output

subCESMulator Hindcasts

Science!

CREDIT Platform for ML Emulation

- a research platform for training, operating, & conducting research with ML models for Earth System science
- **Platform Features**
 - Integrated pre-processing
 - Library of neural network architectures
 - Scalable training and inference on NCAR HPC
 - Physics constraints
 - Analysis tools and plotting

<https://miles.ucar.edu/software/credit/>



Will
Chapman



John
Schreck



DJ
Gagne



Judith
Berner



Kyle
Sha



Arnold
Kazadi



Dhamma
Kimpara



Peter
Lauritzen



Ben
Kirk



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Slide from Will Chapman

