Community Research Earth Digital Intelligence Twin (CREDIT)

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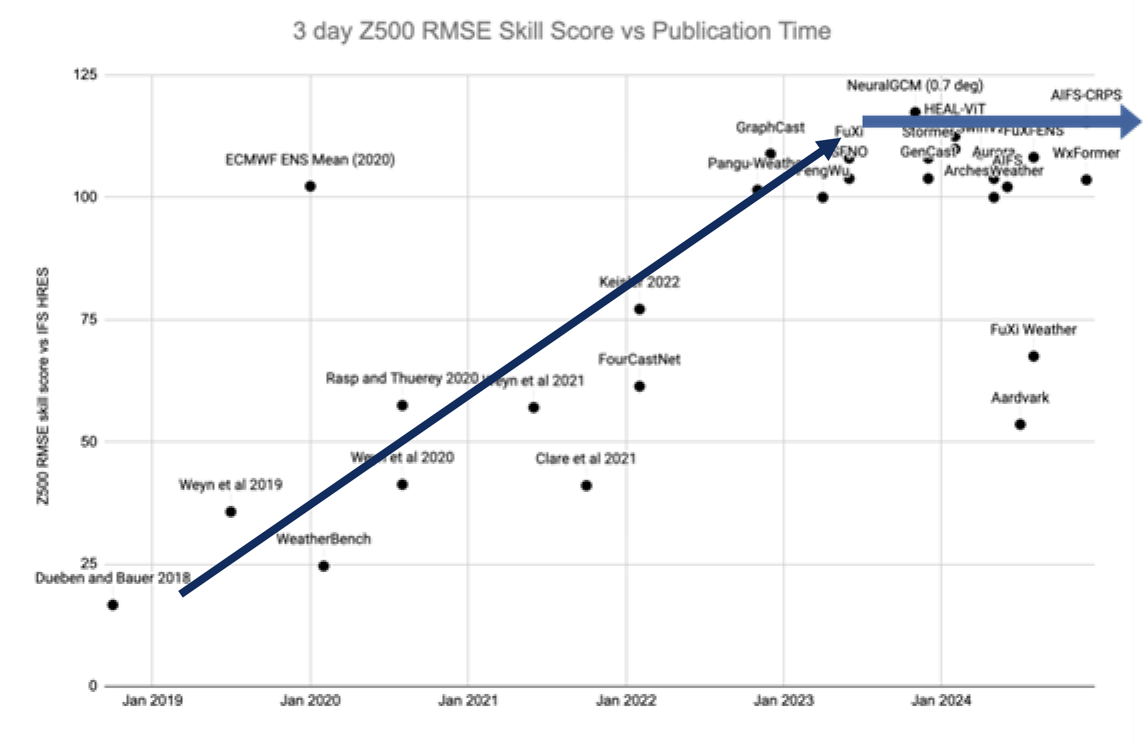
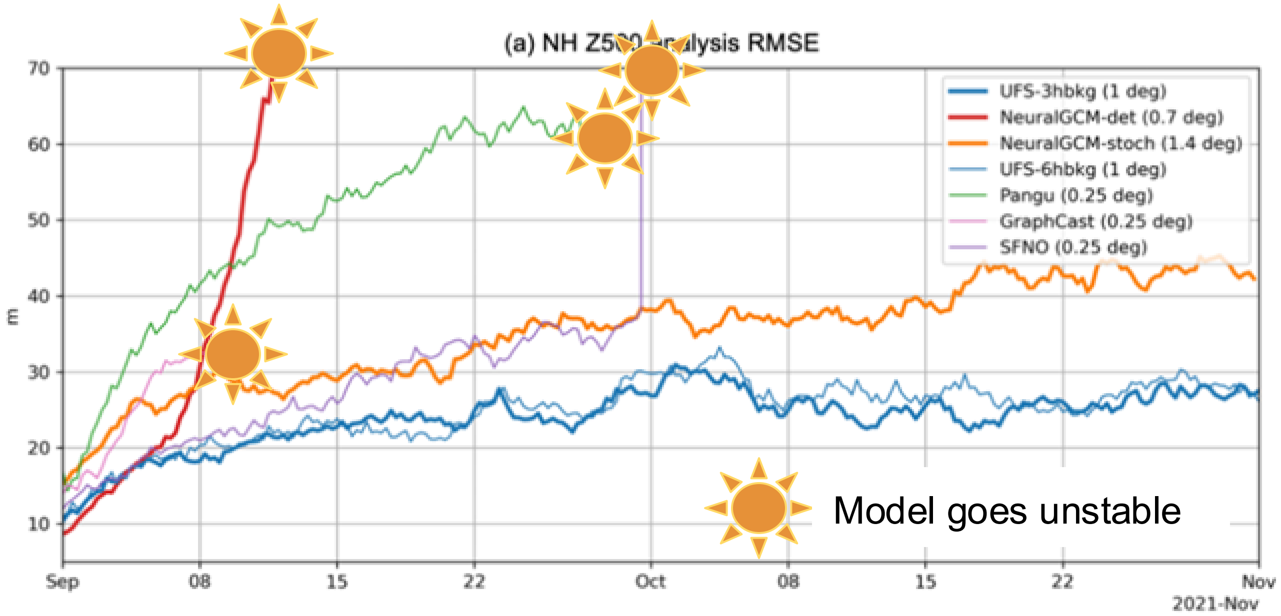
Motivation: Trends in AI Weather Prediction





Source: Slivinski et al. 2024

After 4 years of rapid advancement in accuracy, further advancements in AI weather modeling have shown diminishing returns in improving global metrics.

Experiments with data assimilation and ensembles have revealed physical inconsistencies and instabilities that require more engagement with the data and physics to address.

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.

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
- Community Atmosphere Model
- GFS
- CONUS 404

Models

- WXFormer
- NCAR FuXi
- Graph GRU Net

Physics

- Mass Conservation
- Energy Conservation
- Moisture Budget

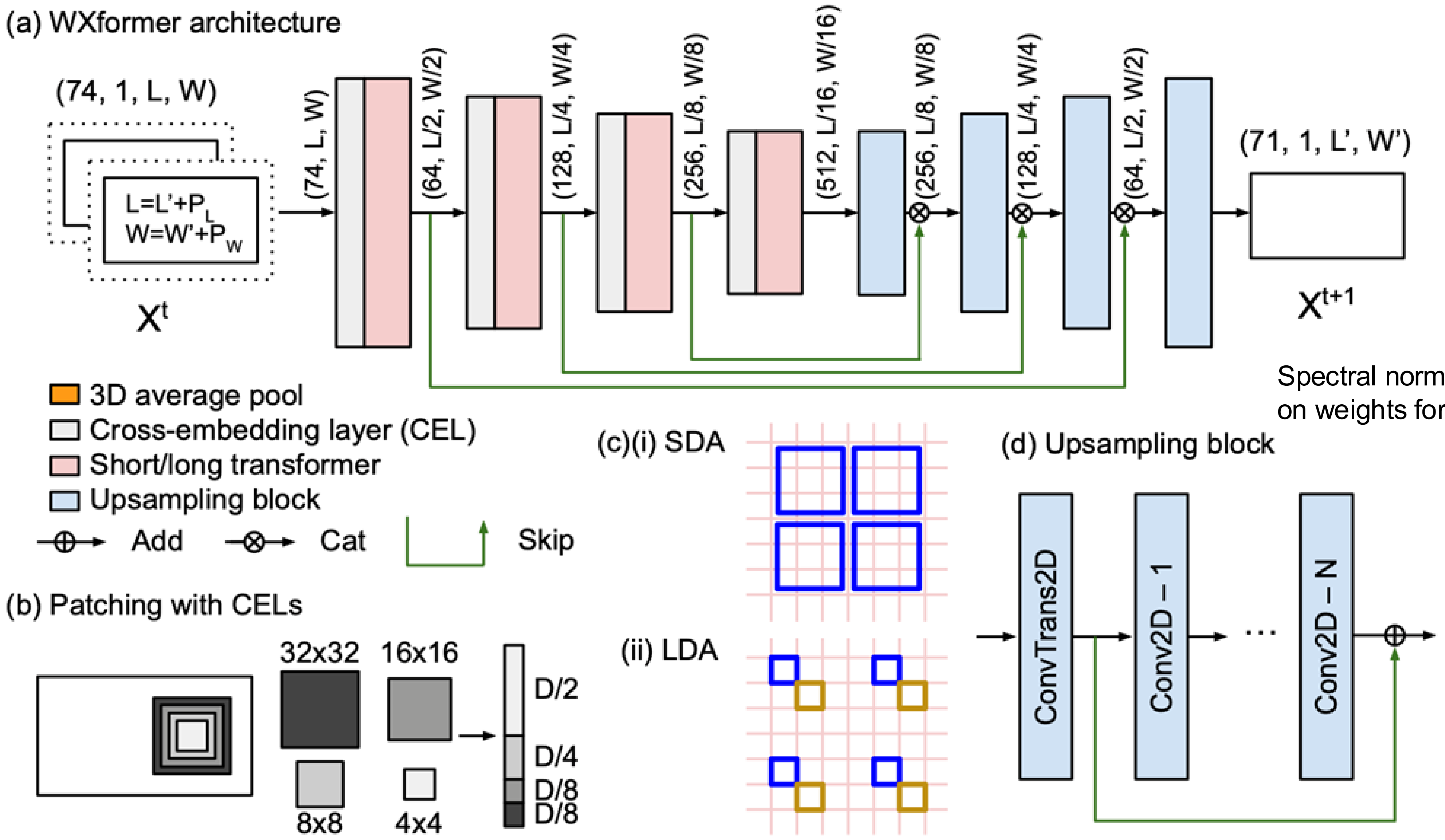
CREDIT WXFormer v1: Training Data

- ERA5 model level data on 0.28 degree grid (1280 x 640 grid cells)
  - 1979-2014 training
  - 2014-2017 validation
  - 2018-2022 testing
- State variables on 16 hybrid-sigma levels sampled from the 137 original levels
- Integrated solar irradiance at top of atmosphere calculated based on ERA5 solar constants and pvlib-python SPA 1-minute solar position calculations

Table 1: Input Variables and Their Units

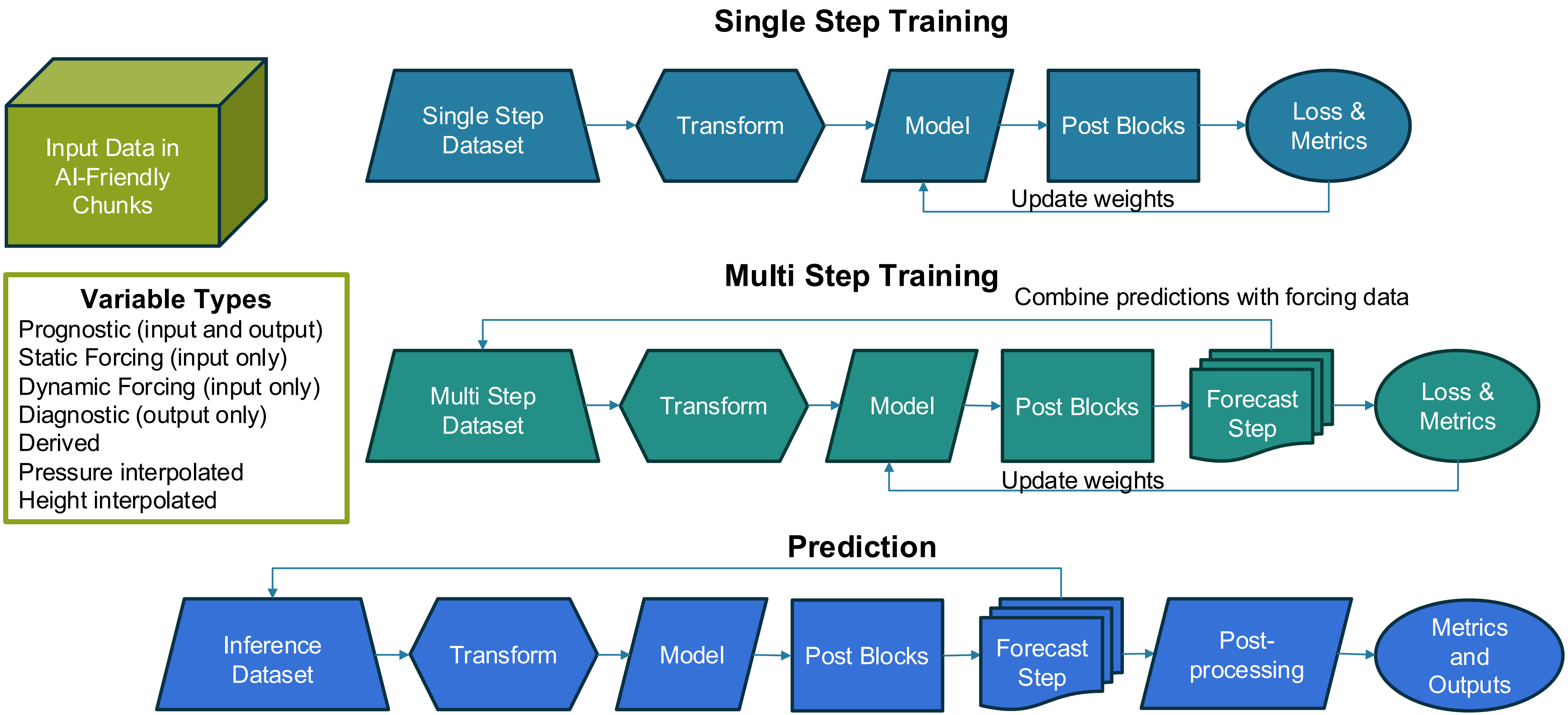
Type	Variable Name	Short Name	Units	Usage
Model level variable	Zonal Wind	U	$m \cdot s^{-1}$	Prognostic
Model level variable	Meridional Wind	V	$m \cdot s^{-1}$	Prognostic
Model level variable	Air Temperature	T	K	Prognostic
Model level variable	Specific Humidity	Q	$kg \cdot kg^{-1}$	Prognostic
Single level variable	Surface Pressure	SP	Pa	Prognostic
Single level variable	2-Meter Temperature	t2m	K	Prognostic
Single level variable	Meridional Wind at 500 hPa	V500	$m \cdot s^{-1}$	Prognostic
Single level variable	Zonal Wind at 500 hPa	U500	$m \cdot s^{-1}$	Prognostic
Single level variable	Temperature at 500 hPa	T500	K	Prognostic
Single level variable	Geopotential Height at 500 hPa	Z500	m	Prognostic
Single level variable	Specific Humidity at 500 hPa	Q500	$kg \cdot kg^{-1}$	Prognostic
Invariant variable	Geopotential at surface	Z_{SFC}	$m^2 \cdot s^{-2}$	Input-only
Invariant variable	Land Sea Mask	LSM	n/a	Input-only
Forcing variable	Integrated instantaneous solar irradiance	I_s	$J \cdot m^{-2}$	Input-only

CREDIT WXFormer Model Architecture



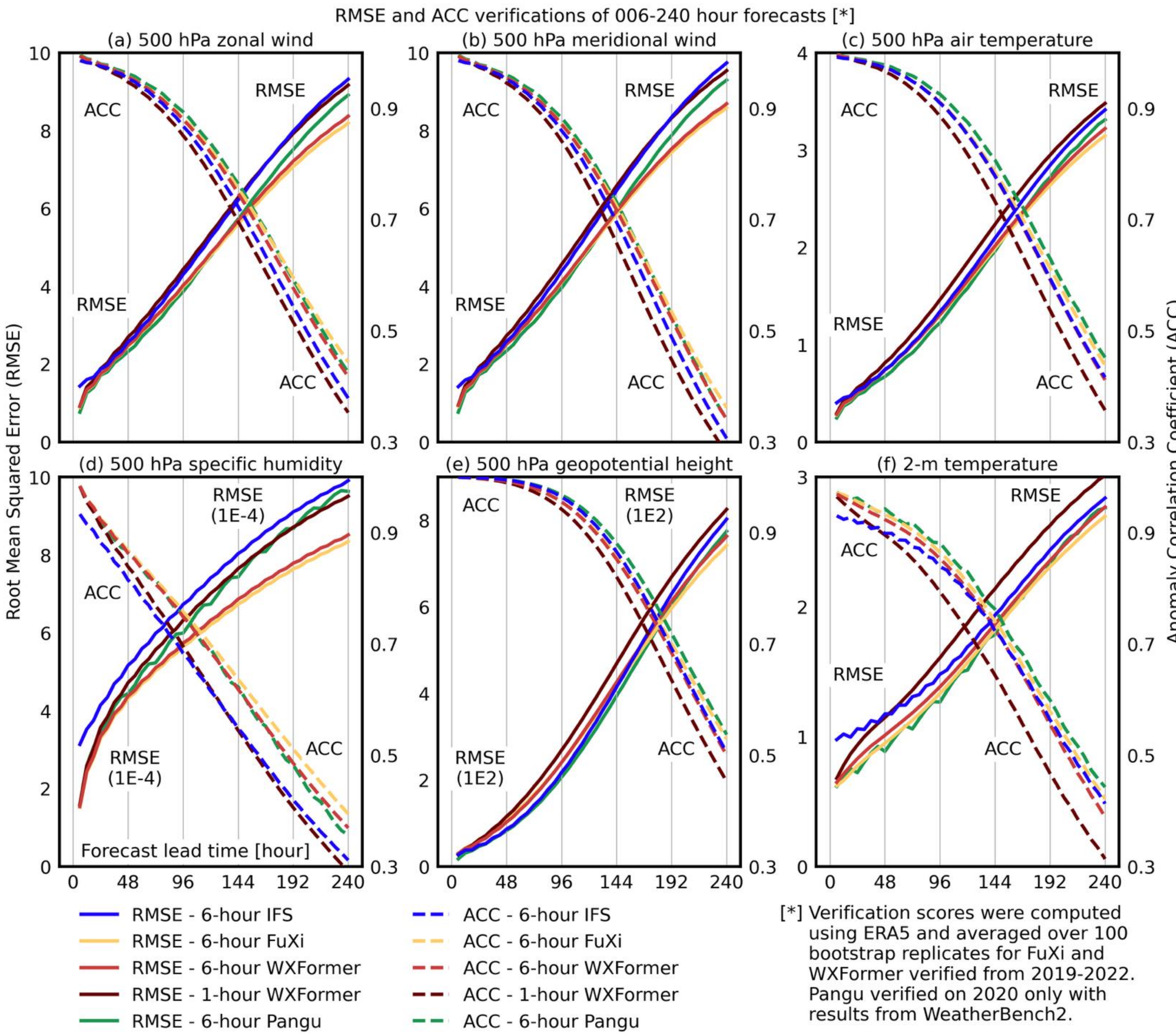
Spectral normalization on weights for stability

CREDIT Components

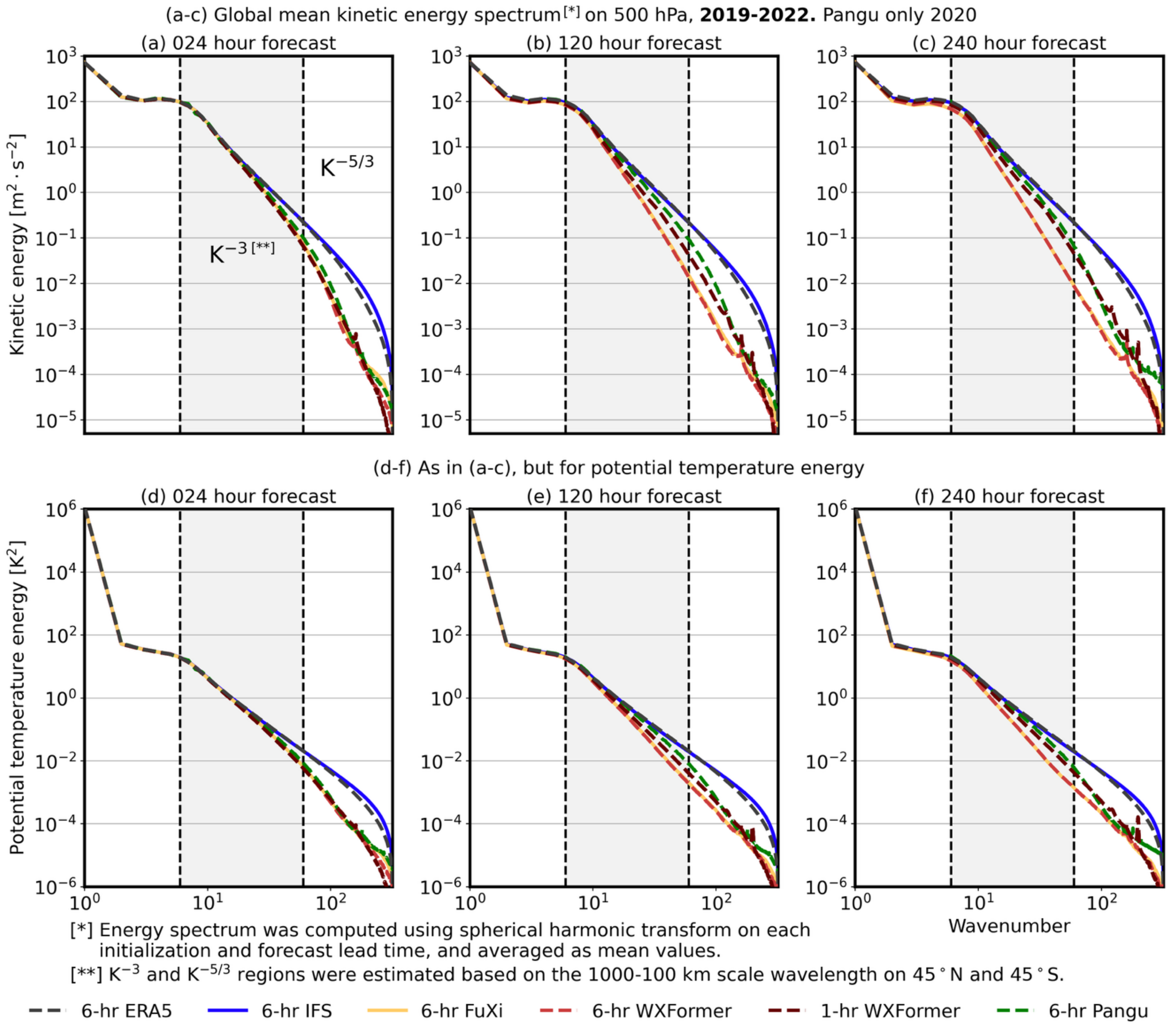


Global Verification: 6 hour Models

- Both WXFormer and MILES FuXi are outperforming IFS for all surface variables
- Larger gains with specific humidity and surface temperature
- Bigger gains at longer lead times
- Performance consistent with other AI NWP models



Kinetic Energy Spectra



Physics Conservation (Work led by Kyle Sha)

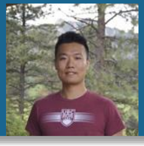
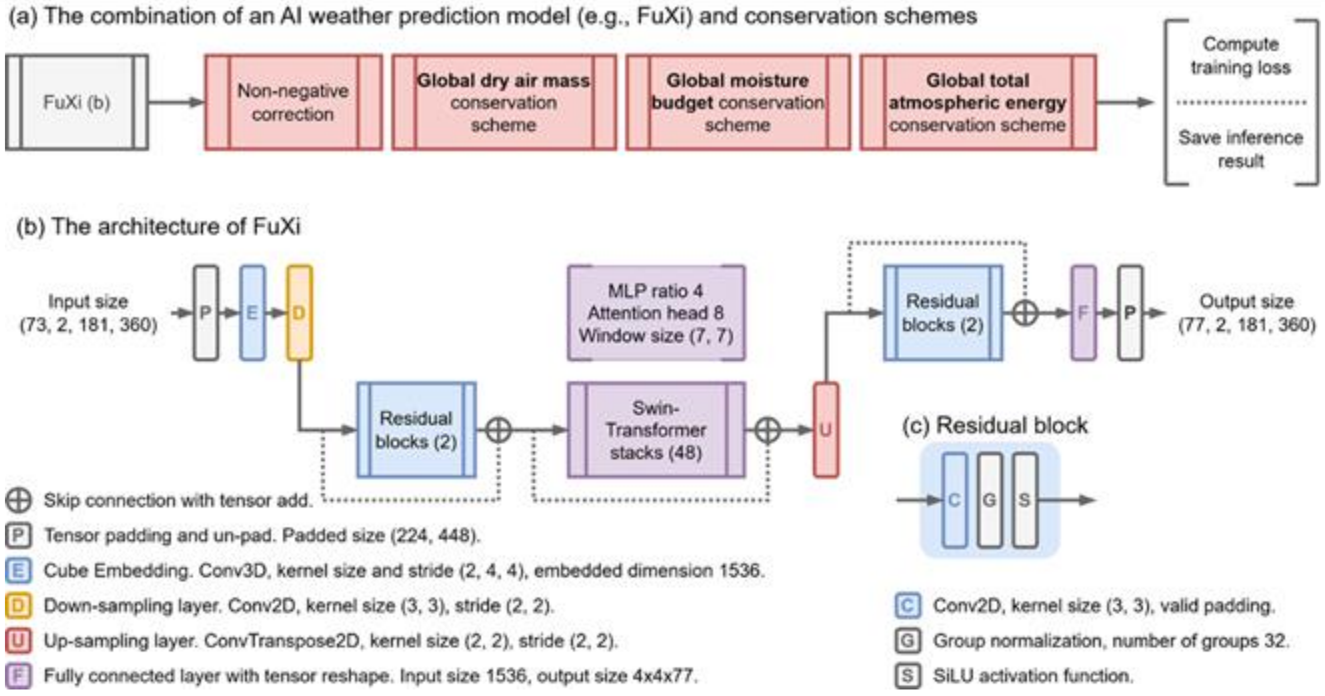


Table 1. The variables of interest in this study.

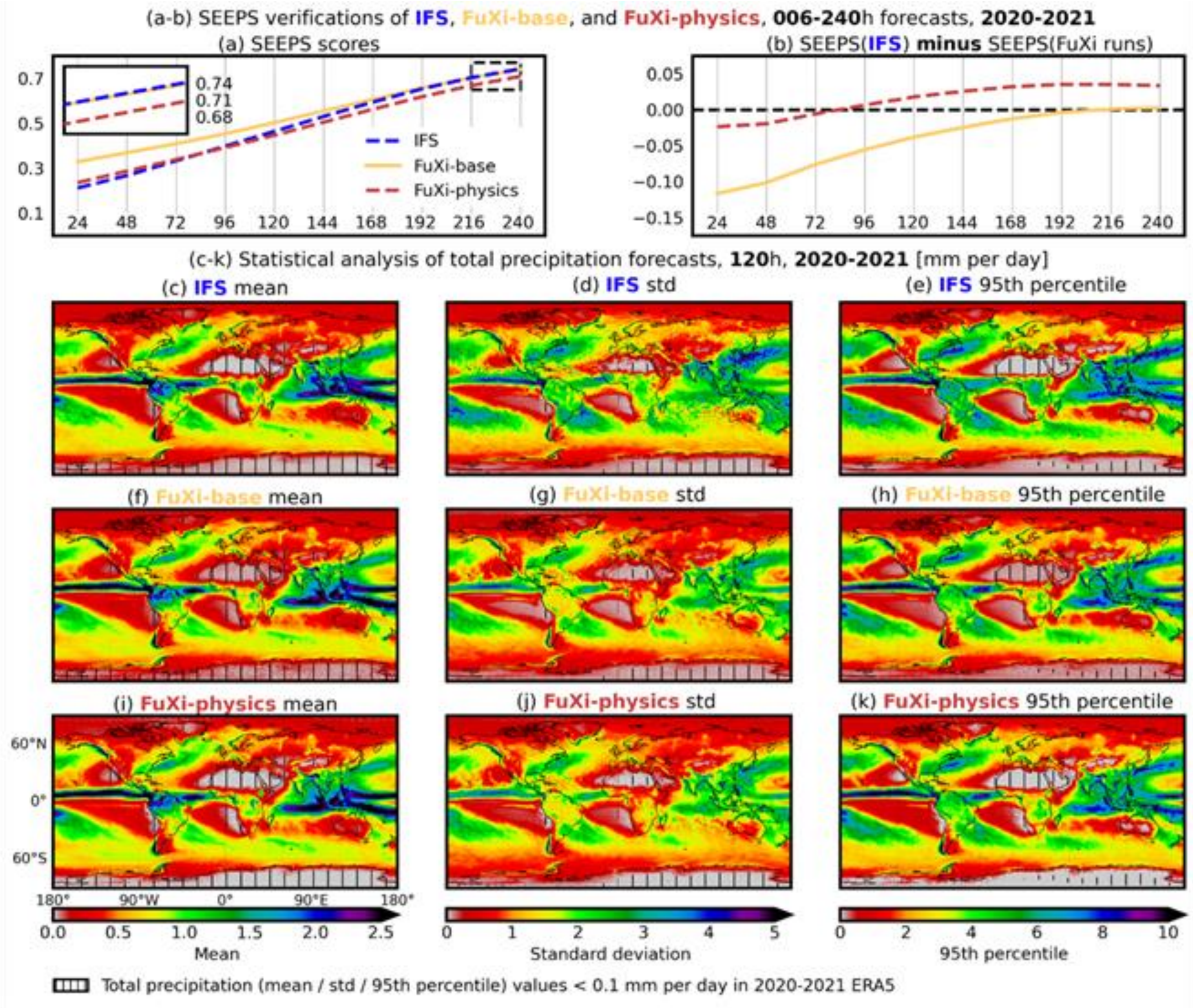
Type	Variable Name	Units	Role
Pressure level	Zonal Wind	$\mathrm{m \cdot s^{-1}}$	Prognostic, Instantaneous
	Meridional Wind	$\mathrm{m \cdot s^{-1}}$	
	Air Temperature	K	
	Specific Total Water[a]	$\mathrm{kg \cdot kg^{-1}}$	
	Geopotential height	m	
Single level	Mean Sea Level Pressure	Pa	Prognostic, Instantaneous
	2-Meter Temperature	K	
	10-Meter Zonal Wind	$\mathrm{m \cdot s^{-1}}$	
	10-Meter Meridional Wind	$\mathrm{m \cdot s^{-1}}$	
Flux form[b]	Total Precipitation	m	Diagnostic, Cumulative
	Evaporation	m	
	Top-of-atmosphere Net Solar Radiation	$\mathrm{J \cdot m^{-2}}$	
	Outgoing Longwave Radiation	$\mathrm{J \cdot m^{-2}}$	
	Surface Net Solar Radiation	$\mathrm{J \cdot m^{-2}}$	
	Surface Net Longwave Radiation	$\mathrm{J \cdot m^{-2}}$	
	Surface Net Sensible Heat Flux	$\mathrm{J \cdot m^{-2}}$	
	Surface Net Latent Heat Flux	$\mathrm{J \cdot m^{-2}}$	
	Top-of-atmosphere Incident Solar Radiation	$\mathrm{J \cdot m^{-2}}$	Input-only, Cumulative
Others	Sea-ice Cover	n/a	Input-only, Instantaneous
	Geopotential at the Surface	$\mathrm{m^2 \cdot s^{-2}}$	Input-only, Static
	Land-sea Mask	n/a	Input-only, Static
	Soil Type	n/a	Input-only, Static

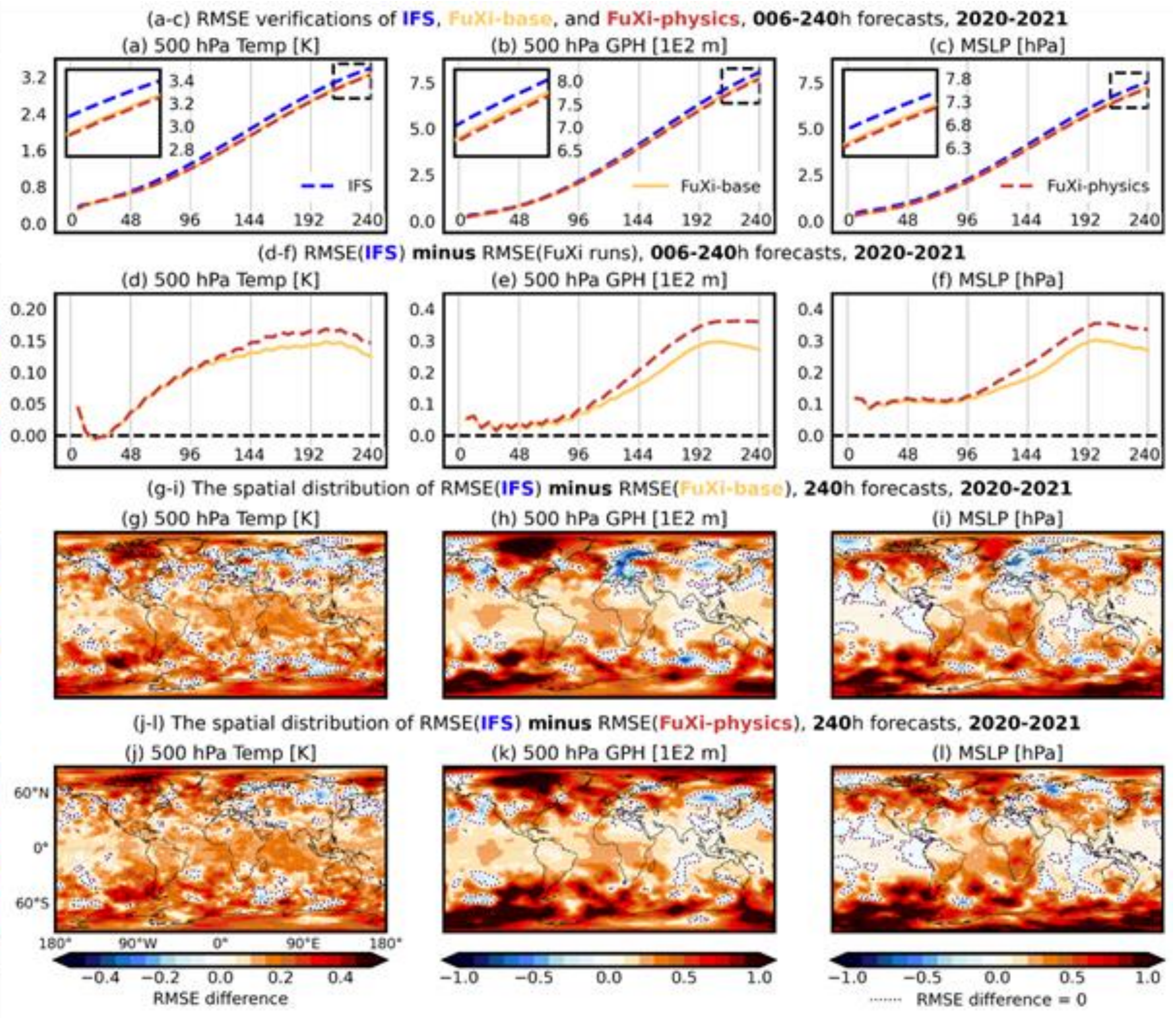
[a] Specific total water is the combination of specific humidity, cloud liquid water content, and rainwater content.
[b] Flux form variables are accumulated every 6 hours. Downward flux is positive.



Data: ERA5 conservatively regridded to 1 degree
Loss: Latitude-weighted MSE
Ingredients for Physics Constraints in AI Weather Prediction
1. Sufficient variables to calculate mass, moisture, and energy budgets
2. Conservation layers that adjust data to conserve mass, moisture, and total energy across the globe to match initial values with multiplicative scaling

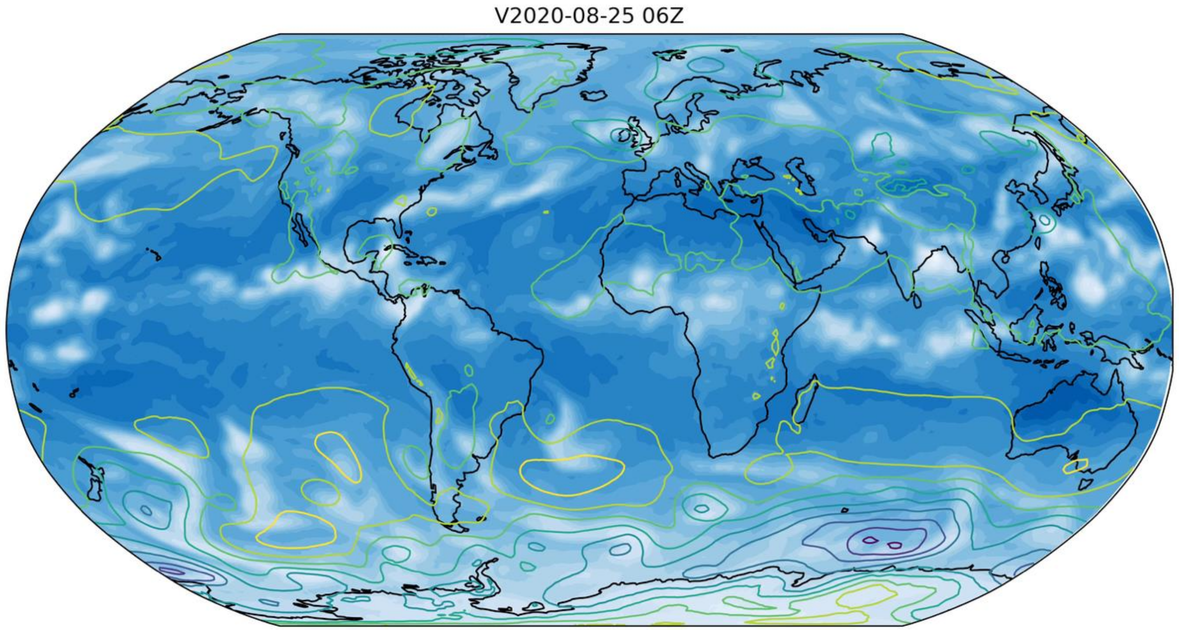
Forecast Improvements



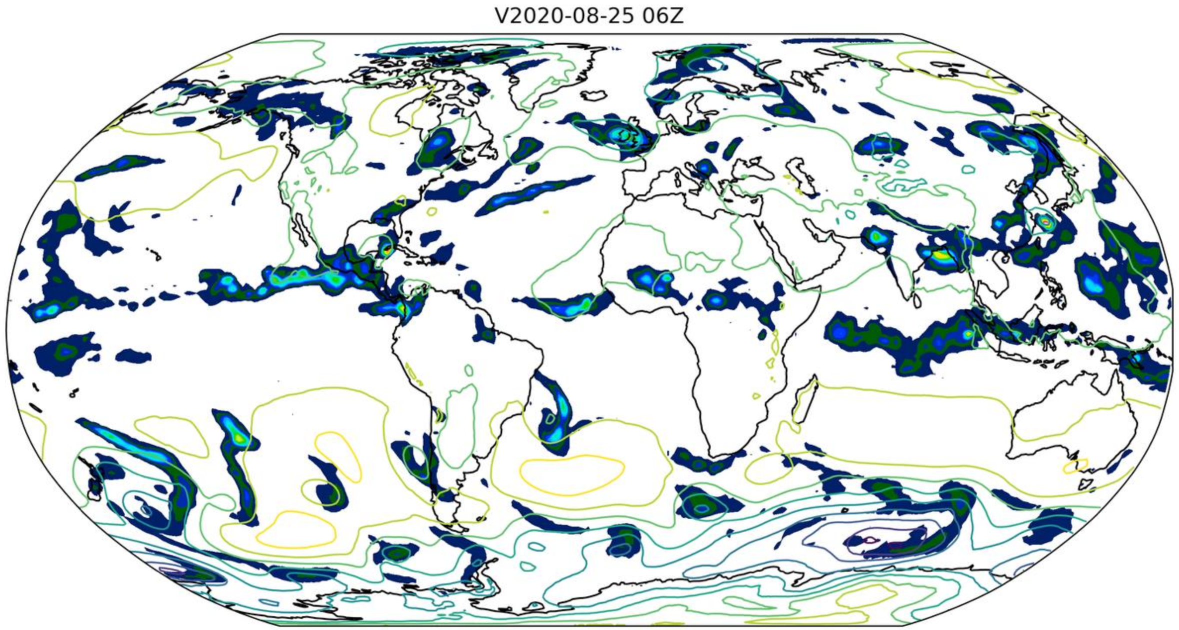


Physics-Constrained Case Example

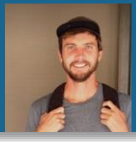
Top of atmosphere net thermal radiation

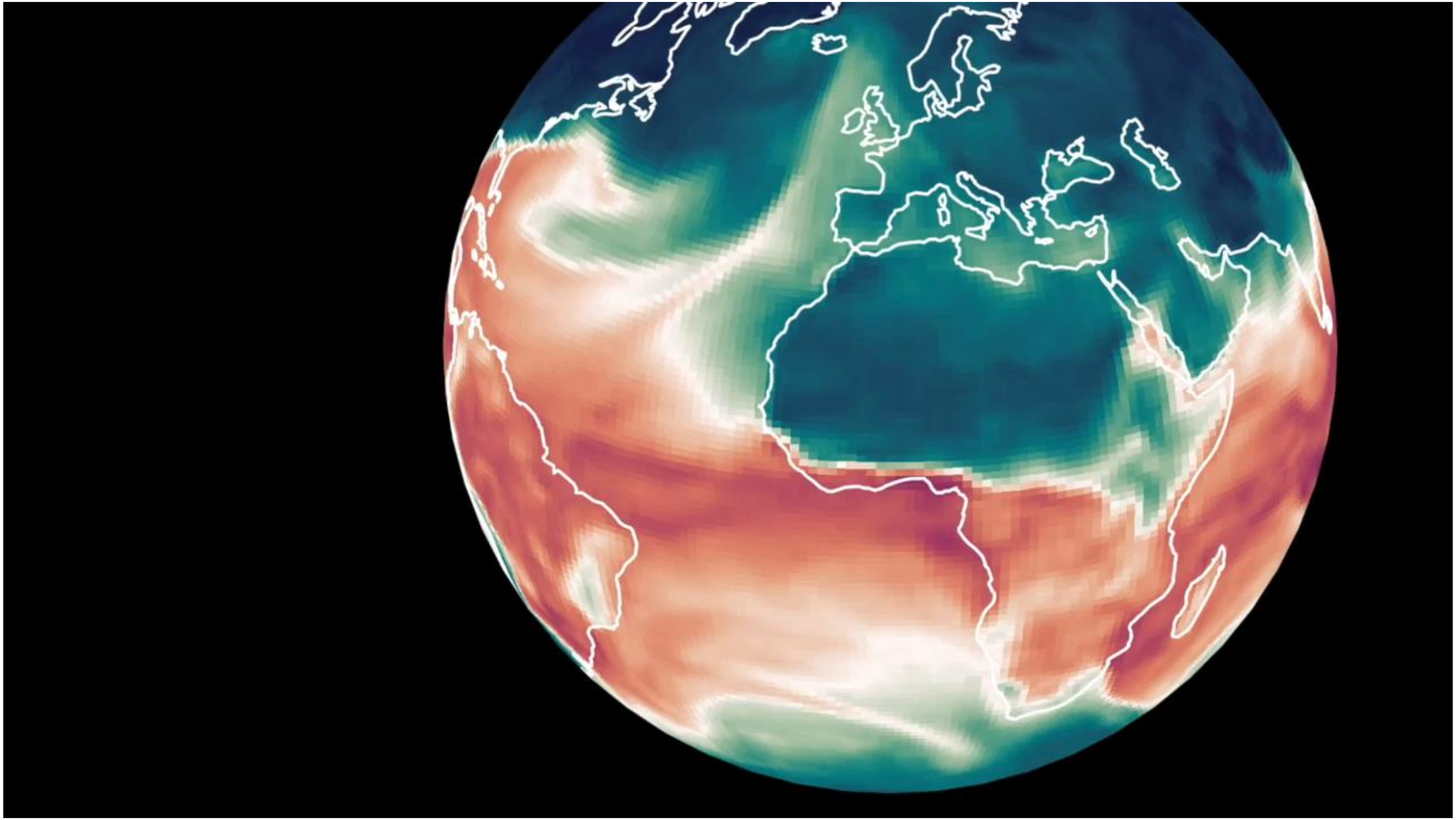


Total Precipitation



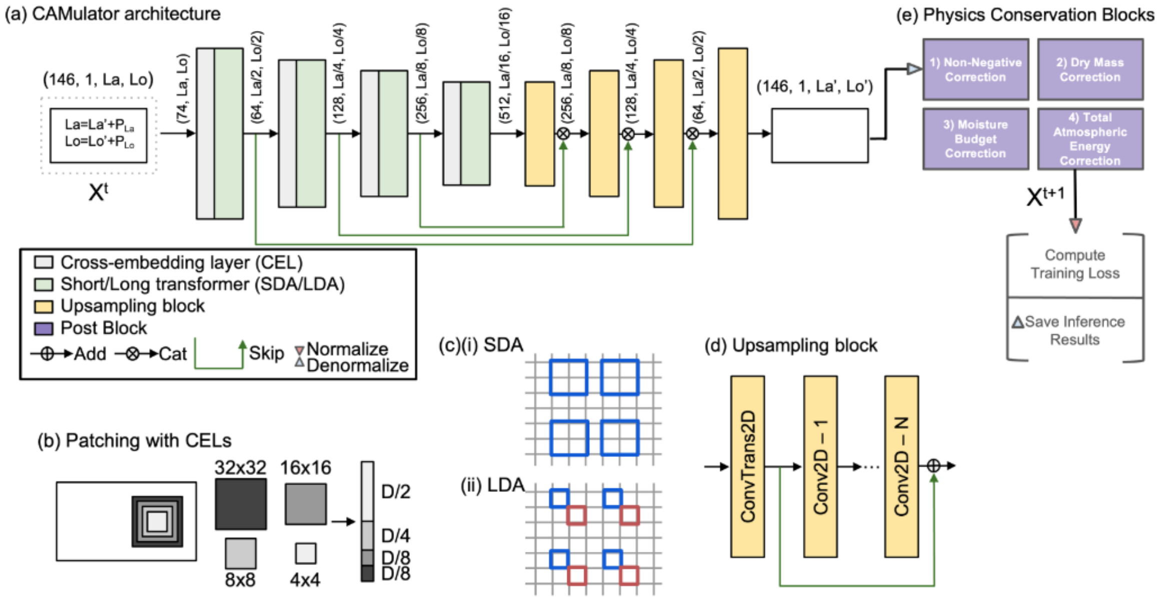
CAMulator (Led by Will Chapman)





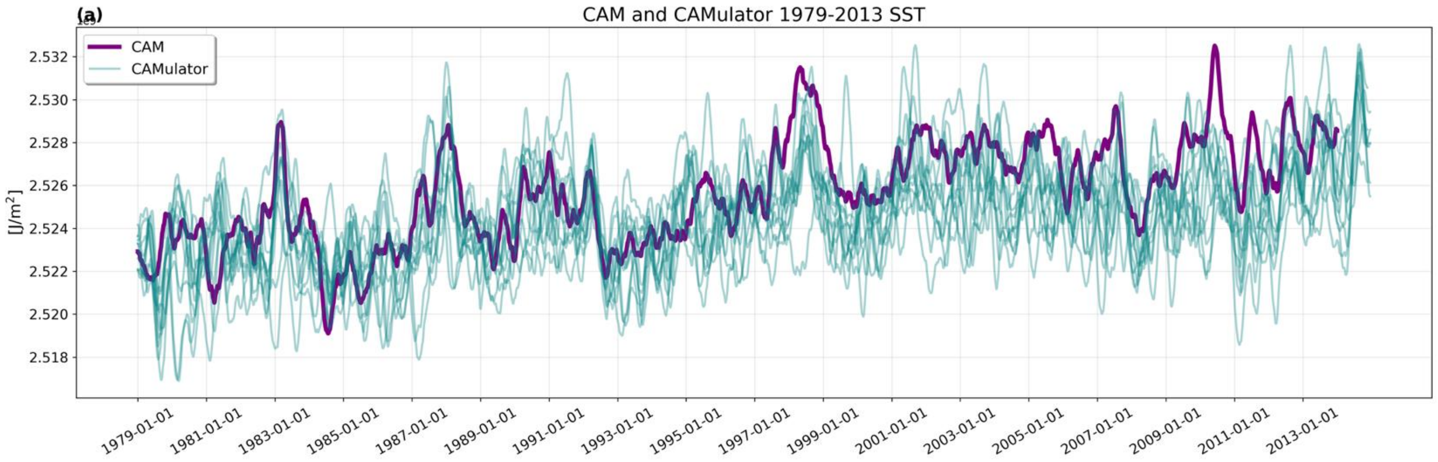
CAMulator Variables and Architecture

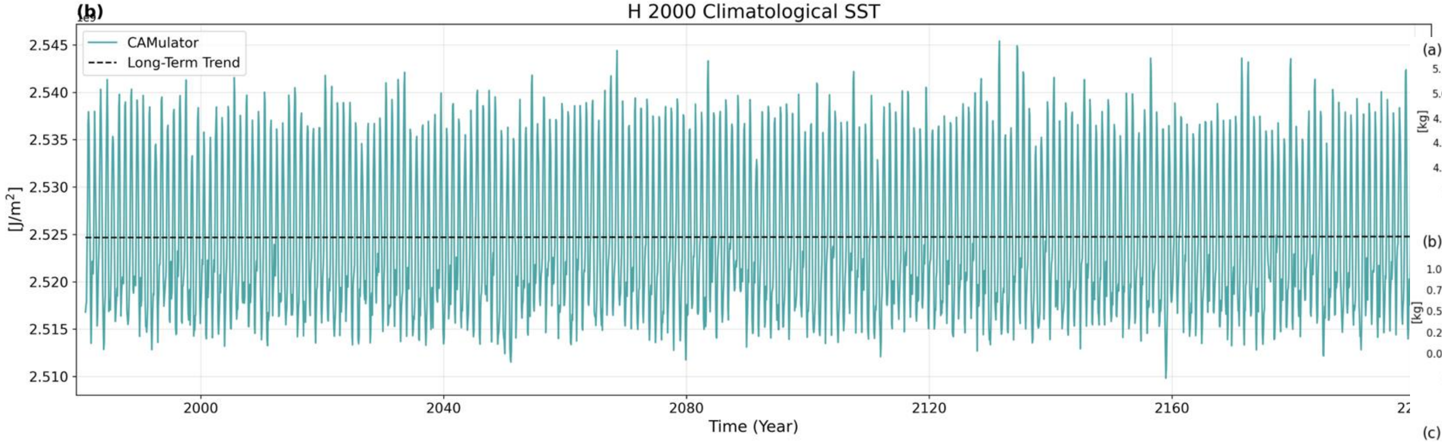
Variable	Description	Units	Levels	Category
Input Variables (Forcing)				
Static Forcing (Time-Invariant Input)				
Surface Geop.	Surface Height	m^2/s^2	Single Level	Input
Land-Sea Mask	Land Mask	Unitless	Single Level	Input
Dynamic Forcing (Time-Varying Input)				
SOLIN	Incoming Solar Radiation	J/m^2	Single Level	Input
SST	Sea Surface Temperature	K	Single Level	Input
Prognostic Variables (Input and Output)				
U	Zonal Wind	m/s	32 Levels	Input/Output
V	Meridional Wind	m/s	32 Levels	Input/Output
T	Temperature	K	32 Levels	Input/Output
*Qtot	Specific Total Water	kg/kg	32 Levels	Input/Output
PS	Surface Pressure	Pa	Single Level	Input/Output
TREFHT	Near-Surface Air Temperature	K	Single Level	Input/Output
Diagnostic Variables (Output Only)				
PRECT	Accumulated Precipitation	m	Single Level	Output
CLDTOT	Total Cloud Cover	Fraction	Single Level	Output
CLDHGH	High Cloud Cover	Fraction	Single Level	Output
CLDLOW	Low Cloud Cover	Fraction	Single Level	Output
CLDMED	Medium Cloud Cover	Fraction	Single Level	Output
TAUX	Zonal Wind Stress	N/m^2	Single Level	Output
TAUY	Meridional Wind Stress	N/m^2	Single Level	Output
U10	10m Wind Speed	m/s	Single Level	Output
QFLX	**Surface Moisture Flux**	m	Single Level	Output
FSNS	**Net Solar Flux** at Surface	J/m^2	Single Level	Output
FLNS	**Net Longwave Flux** at Surface	J/m^2	Single Level	Output
FSNT	**Net Solar Flux** at TOA	J/m^2	Single Level	Output
FLNT	**Net Longwave Flux** at TOA	J/m^2	Single Level	Output
SHFLX	**Sensible Heat Flux**	J/m^2	Single Level	Output
LHFLX	**Latent Heat Flux**	J/m^2	Single Level	Output

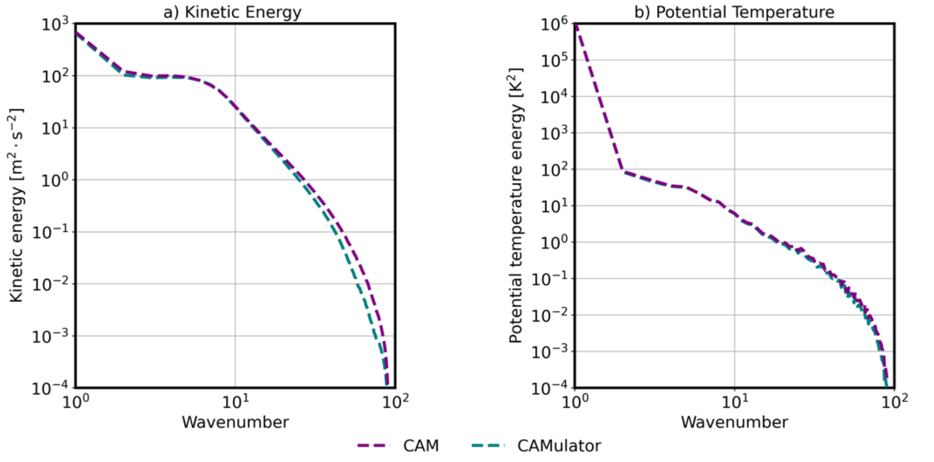


- Trained on CAM over 30 years with SST forcing from observations
- Throughput of 480 Sim. Years/Day

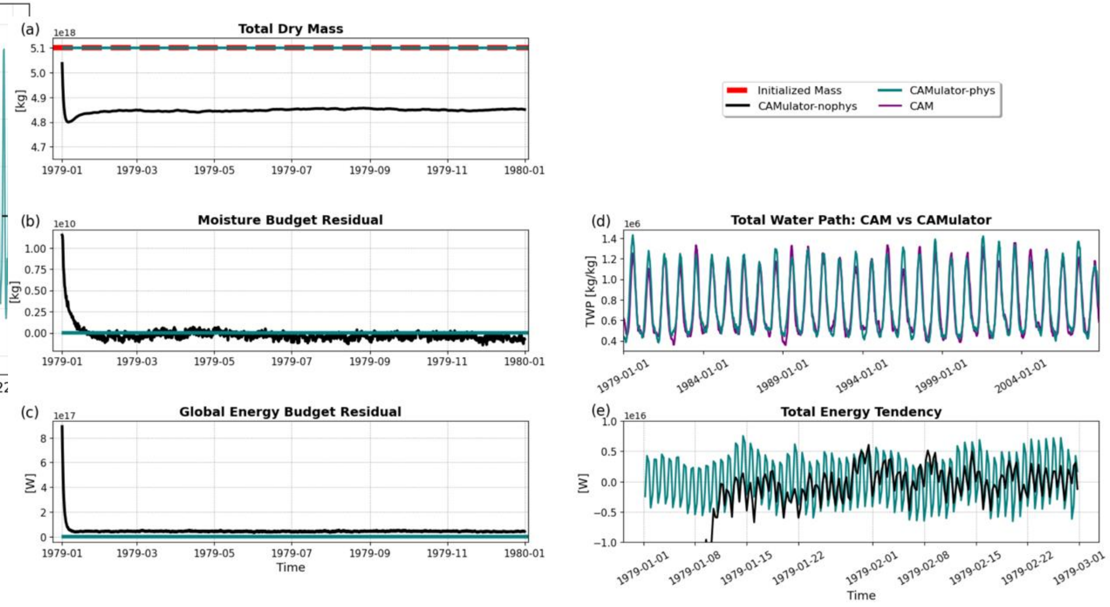
CAMulator Stability



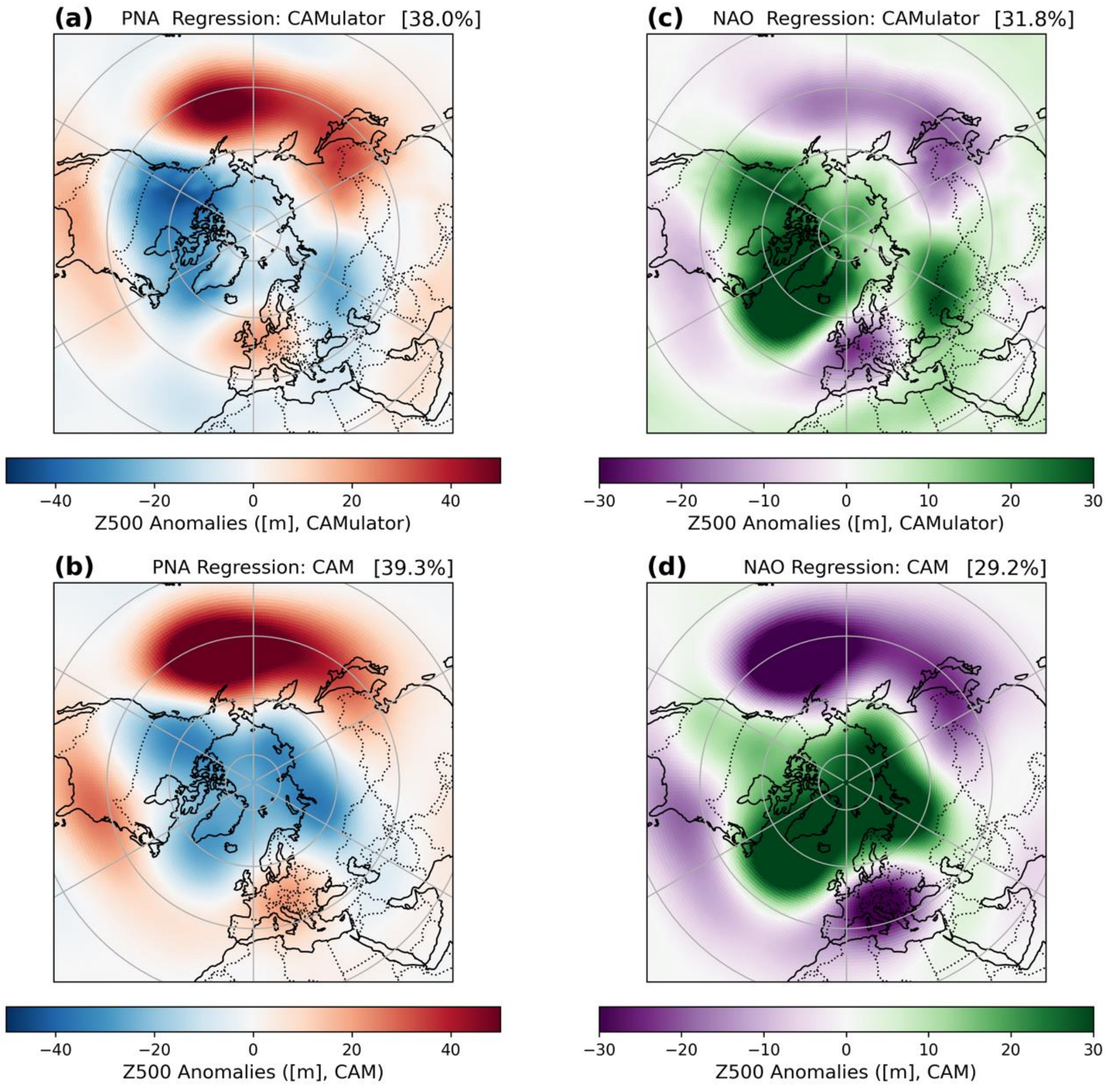


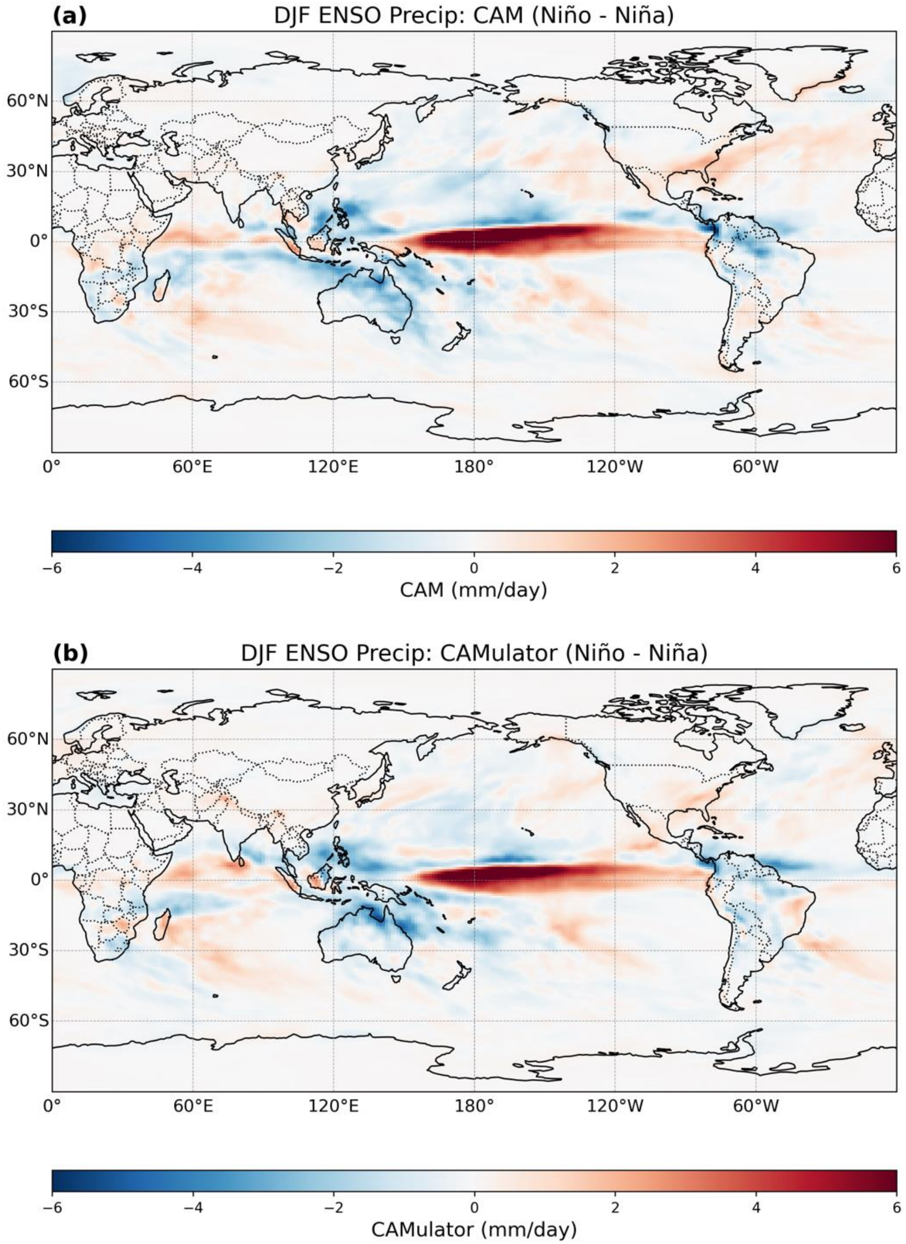


[*] Energy spectrum was computed using spherical harmonic transform on the total rollout and average

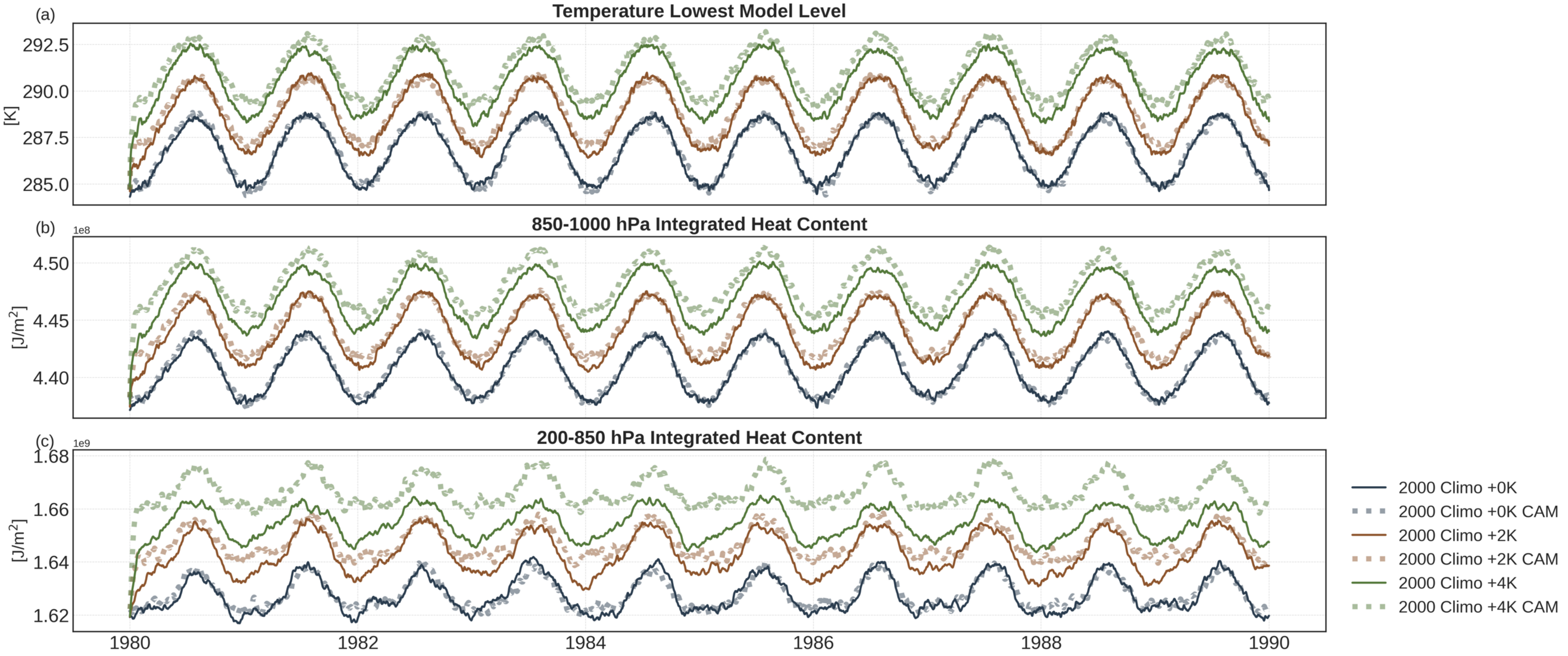


CAMulator Teleconnections

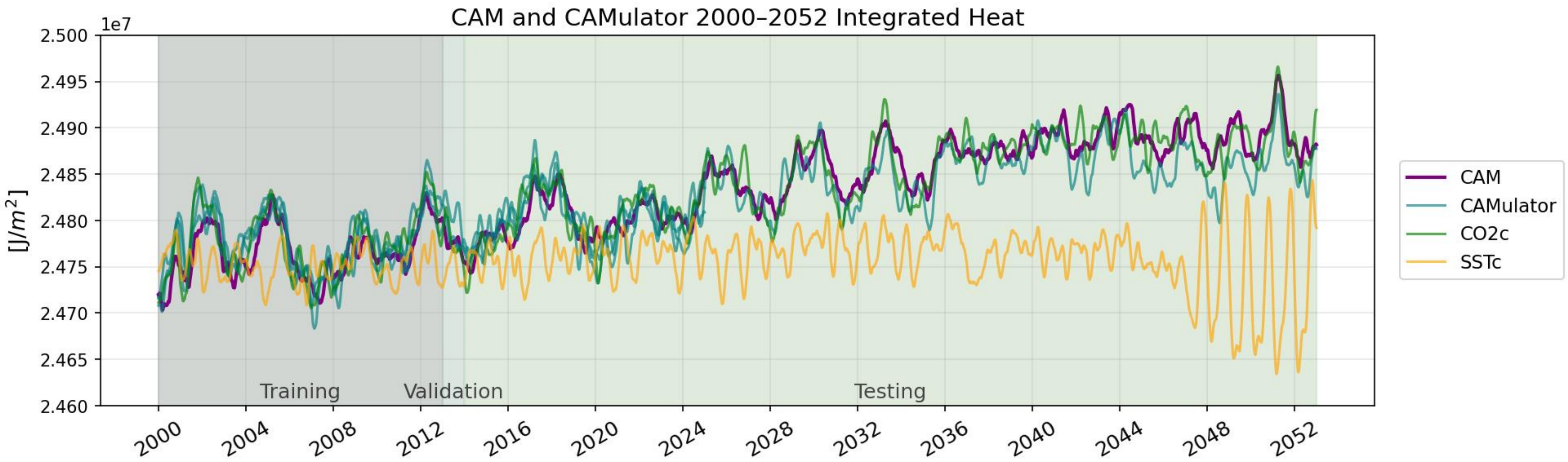




CAMulator SST Forcing Experiments



CAMulator SST and CO2 Forcing Experiments



CREDIT Future Directions

Open Questions

- Ensemble generation: what is the most accurate method with least latency?
- Tradeoffs between data volume, model size, input data size, and types of physical constraints
- Foundation models (e.g. Aurora) vs. more specialized models trained on high quality datasets
- Data assimilation: traditional methods versus DA emulators vs hybrid methods

Next Steps

- Improve usability of CREDIT with software engineering support
- Adding ensemble generation
- Regional model training and evaluation
- S2S and longer scale rollout evaluation
- Training a new weather model with more vertical levels and hourly timestep at 0.25 degree resolution

Summary

- CREDIT opens a new pathway to customization of the whole AI weather and climate modeling pipeline
- Physics constraints and spectral normalization enable more stable rollouts to multi-year time scales
- Extrapolation of climate change signals demonstrated, but causality may not be correct.
- CREDIT source: https://github.com/NCAR/miles-credit
- Links to CREDIT papers: https://miles.ucar.edu/projects/credit/