AI for Climate Modeling: Present and Future

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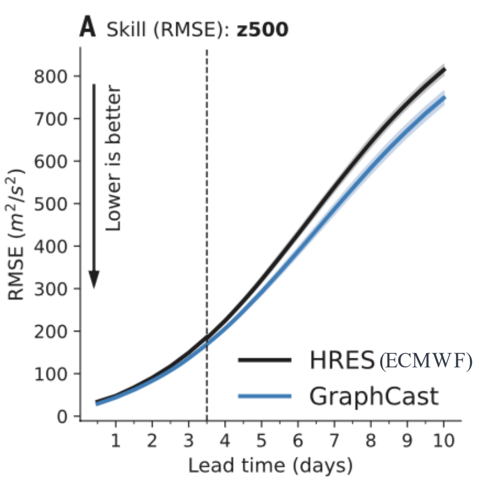
External partners

M^{2}LInES | GFDL | LLNL

ML-based weather forecasts are state of the art

- **2019–2022:** pioneering work showing potential for ML-based global weather forecasting trained on reanalysis (e.g. *Dueben and Bauer, Weyn et al. DLWP*)
- **2022–2023:** Pangu, GraphCast, etc. demonstrate improved 3-10 day deterministic weather prediction over operational benchmarks
- **2024–:** development of probabilistic (e.g. GenCast) and ocean-atmosphere models (ORCA, OLA). ECMWF develops AIFS



GraphCast: Lam et al., 2023 (*Science*)

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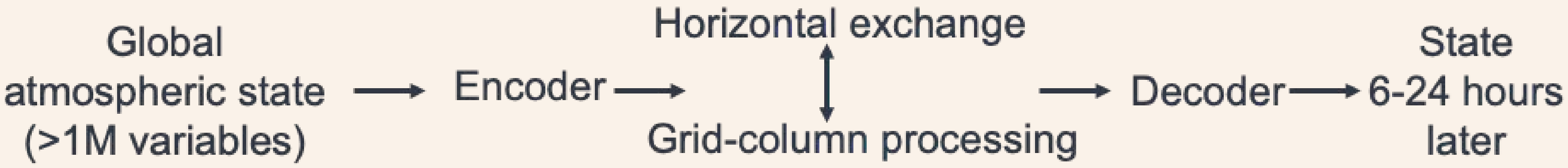
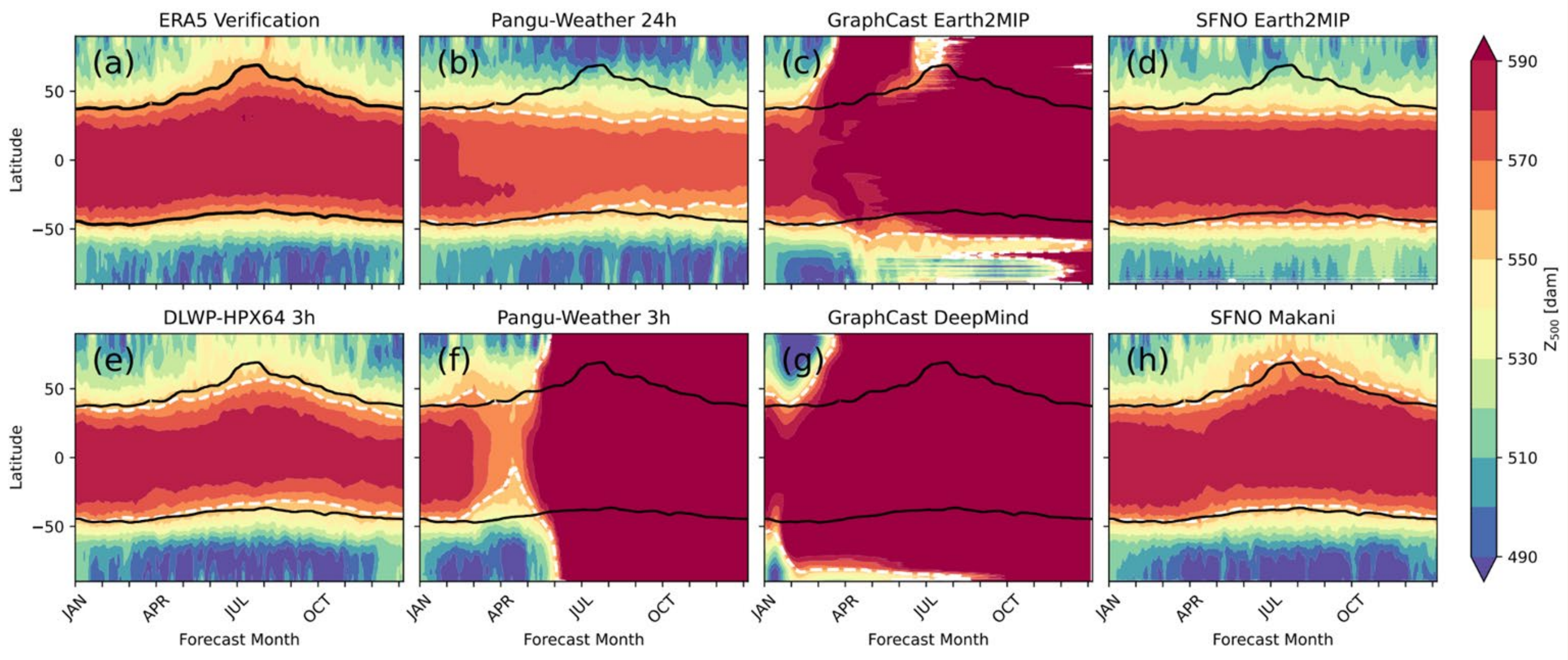
Diverse ML architectures used for weather forecasts



- U-Nets, Graph neural nets, neural operators, SWIN transformers, diffusion models
- 10^6 - 10^9 learnable weights
- Train on 40 years of ERA5 in days to weeks
- 10-day forecast on a single GPU in a few seconds
- Large efficiency gains from long time step and GPU-optimized matrix math

Existing ML forecasts are often not stable and/or accurate beyond ~2 weeks



Karlbauer et al. 2024; https://arxiv.org/abs/2311.06253

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Weather vs. climate emulation

- ML weather emulators are trained on decades of global atmospheric observations (‘reanalysis’), which are most reliable since 1980
- The goal of climate models is to predict past and future climates that may lie well outside this historical range.
- Data-driven ML models are generally unreliable for extrapolation, because they are not directly grounded in physical principles.
- Ai2 CM goal: Train an ML emulator of an excellent high-resolution physically-based global climate model for 100-10000x speedup of routine simulations, ensembles, downscaling…
- This may also help us tackle the grander challenge: how to develop data-driven, physics-informed AI climate models that generalize across unseen climates.

Our approach: ACE (Ai2 Climate Emulator)

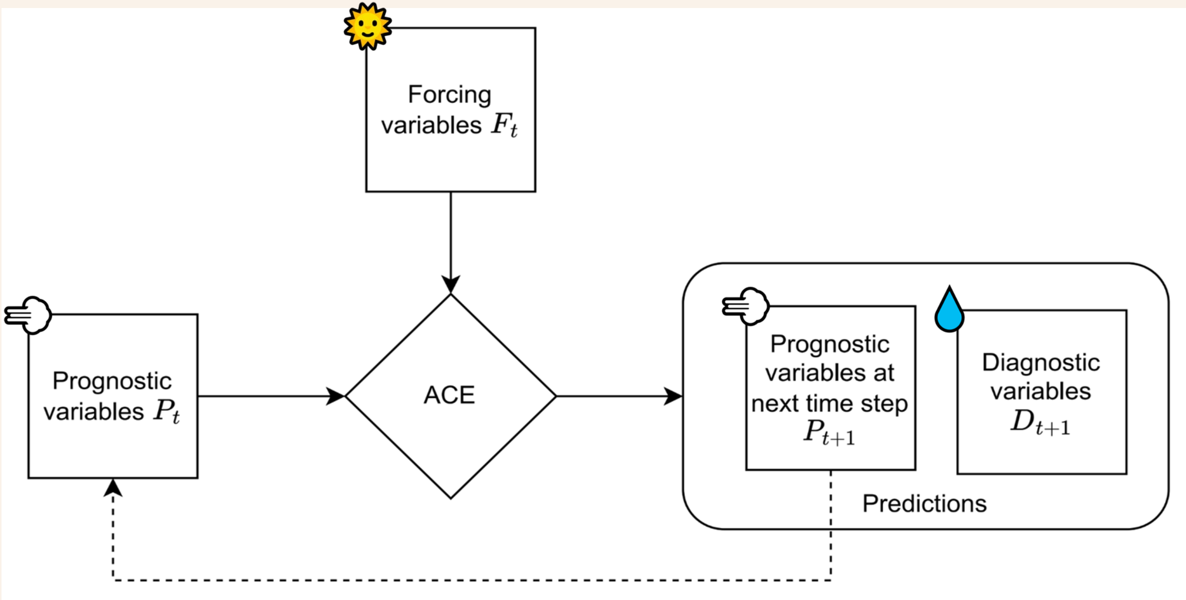
- Derive climate as statistics of simulated weather, like physics-based GCMs. We only learn 6-hour atmospheric state update; good climate not assured!
- Train on climate model output, not just ERA5
  - Want to use data from diverse range of climates (global warming etc.)
- Start simple, then increase complexity:
  - Use relatively coarse 1° (100 km) grid and 8 terrain-following layers
  - ACE v1: Climatological SST and fixed external forcing
  - ACE2: More realistic forcings (historical SST, slab ocean model + CO_2)
- Ongoing progress:

Our variable set

🌬️ **Prognostic** :
→ horizontal winds, temperature, specific total water, skin temperature of land/sea-ice, surface pressure

🌞 **Forcing** :
→ insolation, sea surface temperature, surface type fractions, elevation, [CO_2]

💧 **Diagnostic** :
→ precipitation, TOA and surface radiative fluxes, surface turbulent heat/moisture fluxes

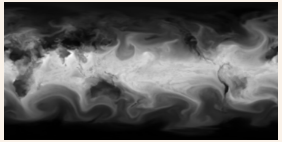


Training Setup

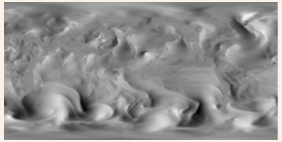
Loss function: mean-squared error of 6-hour forecast computed over all the output variables (for ACE2, accumulated over 2 forward steps)

Input at time t

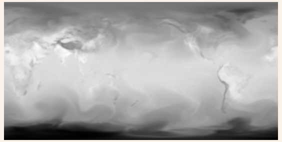
Humidity



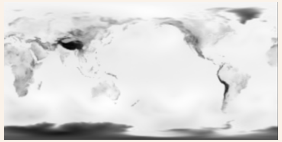
Wind



Temperature

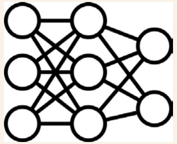


Surface pressure



(**forcing** + **prognostic** vars) x 180 x 360

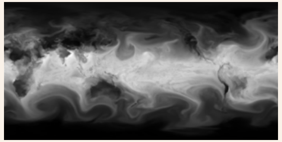
SFNO*



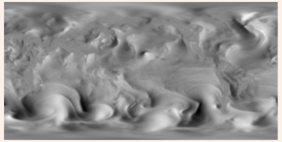
$$f(\mathbf{u}; \theta)$$

Prediction of $t + 6$ hours

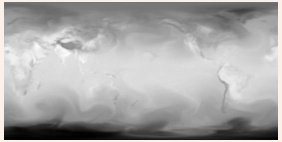
Humidity



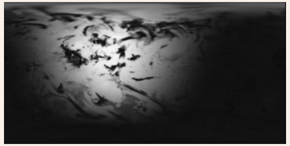
Wind



Temperature



Down SW sfc rad flux



(**prognostic** + **diagnostic** vars) x 180 x 360

Showing subset of inputs/outputs

***SFNO**: Spherical Fourier Neural Operator from Bonev et al., 2023 arxiv.org/abs/2306.03838

ACE training data

Train ACE on 6-hourly 3D output from NOAA FV3GFS/SHiELD atmos. model on C96 (100 km) grid.

Regrid to 8 layers on a 1° Gaussian lat/lon grid for SFNO compatibility, speed, compactness

Reference datasets:

1. **ACE**: Annually-repeating SST forcing (climSST)
   - 100 years of training data, 10 years of validation
   - Each year is an independent sample of the same climate forcing

1. **ACE2**: Historical SSTs (AMIP)
   - ERA5 or an SHiELD AMIP ensemble, 1940-2020

2. **ACE2-SOM**: Slab ocean with CO_2 forcing
   - Present-day CO_2, 2xCO_2 and 4xCO_2 (50 yrs each) with a simple slab ocean

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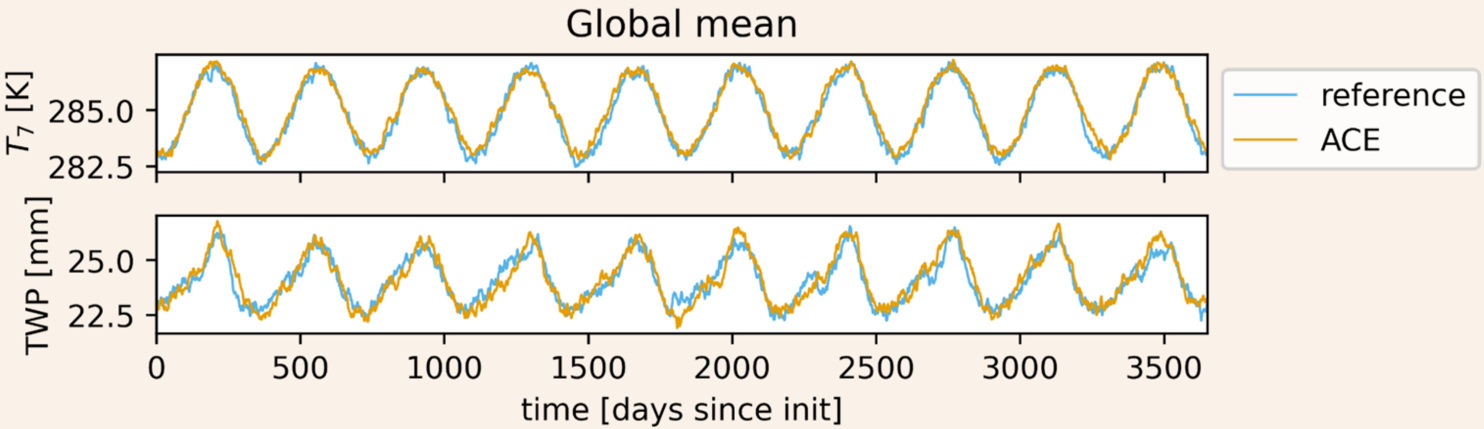
ACE v1: Stable, accurate seasonal cycle!

Temperature
(boundary
layer average)

Total Water Path
(vertically integrated
moisture)



Indefinitely stable far as we can tell
Remarkable accuracy given ACE is trained only to make good 6-hr forecasts
800 simulated years/day on one A100 GPU

Watt-Meyer et al. (2023)

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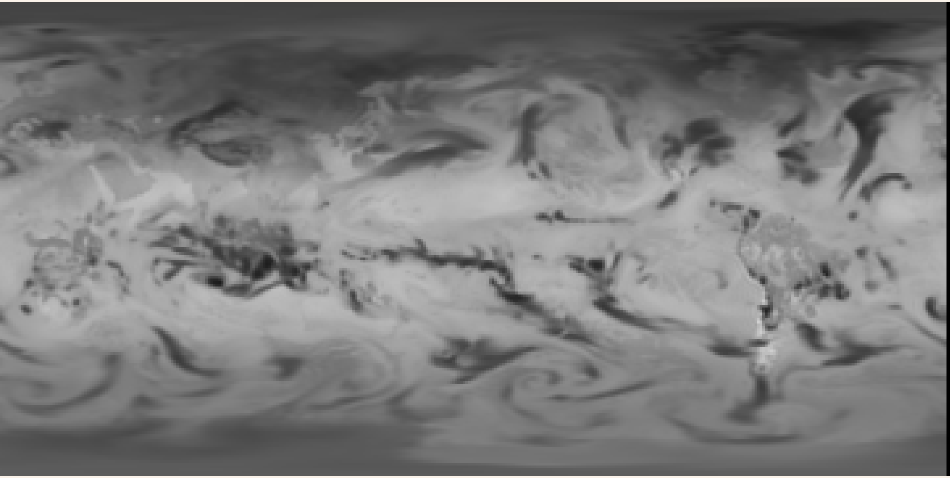
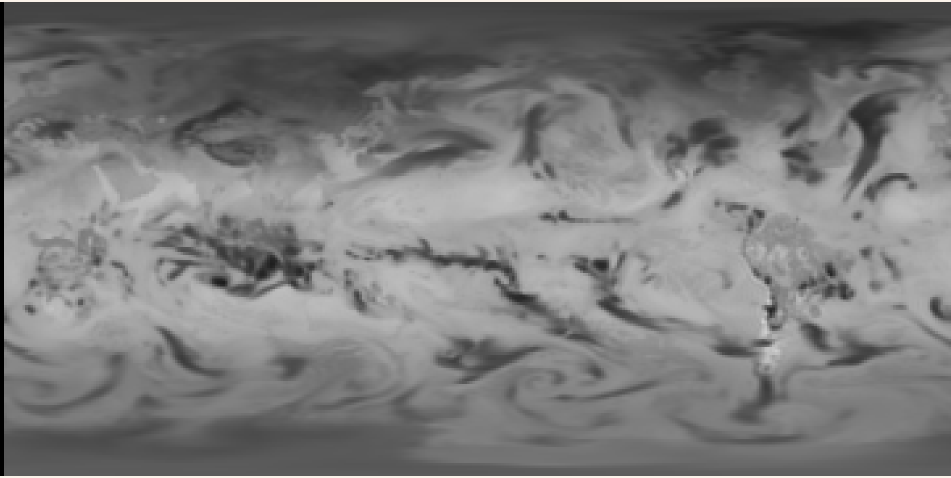
Realistic weather variability

Outgoing longwave radiation (OLR) for first 100 days of simulation

ACE (prediction)



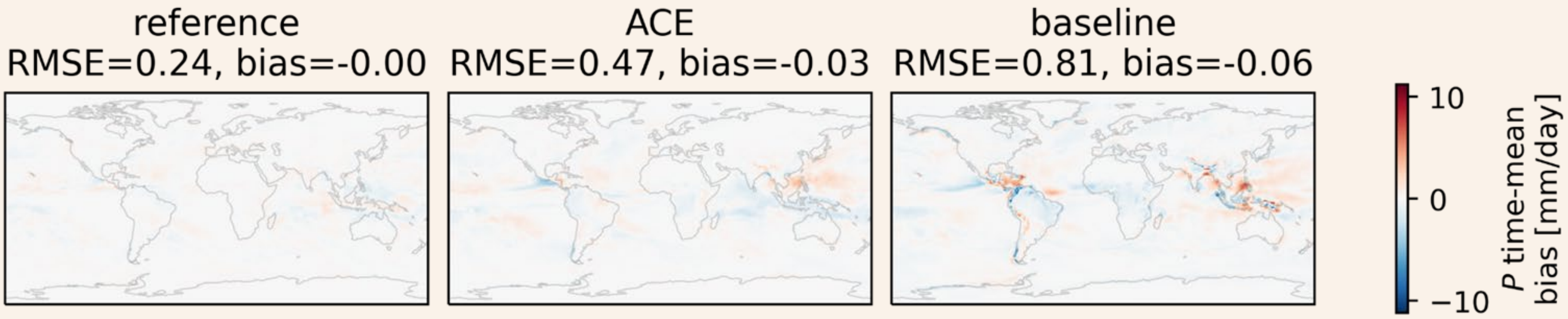
FV3GFS (target)



Mostly realistic OLR despite model not explicitly prognosing clouds!
But also see evidence of overly smooth prediction.

Excellent climate accuracy

10 year time-averaged precipitation rate bias



Natural variability of the system (noise floor)

2x coarser physics-based model

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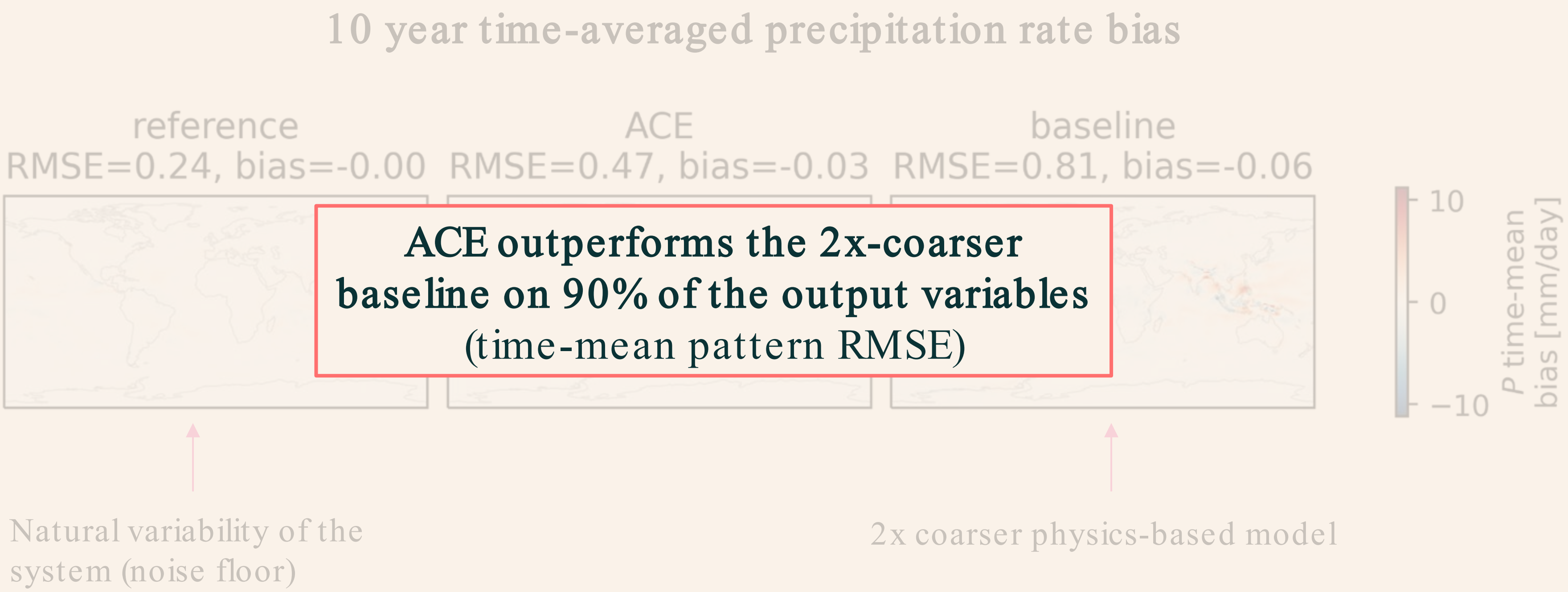
Watt-Meyer et al. (2023)

Excellent climate accuracy

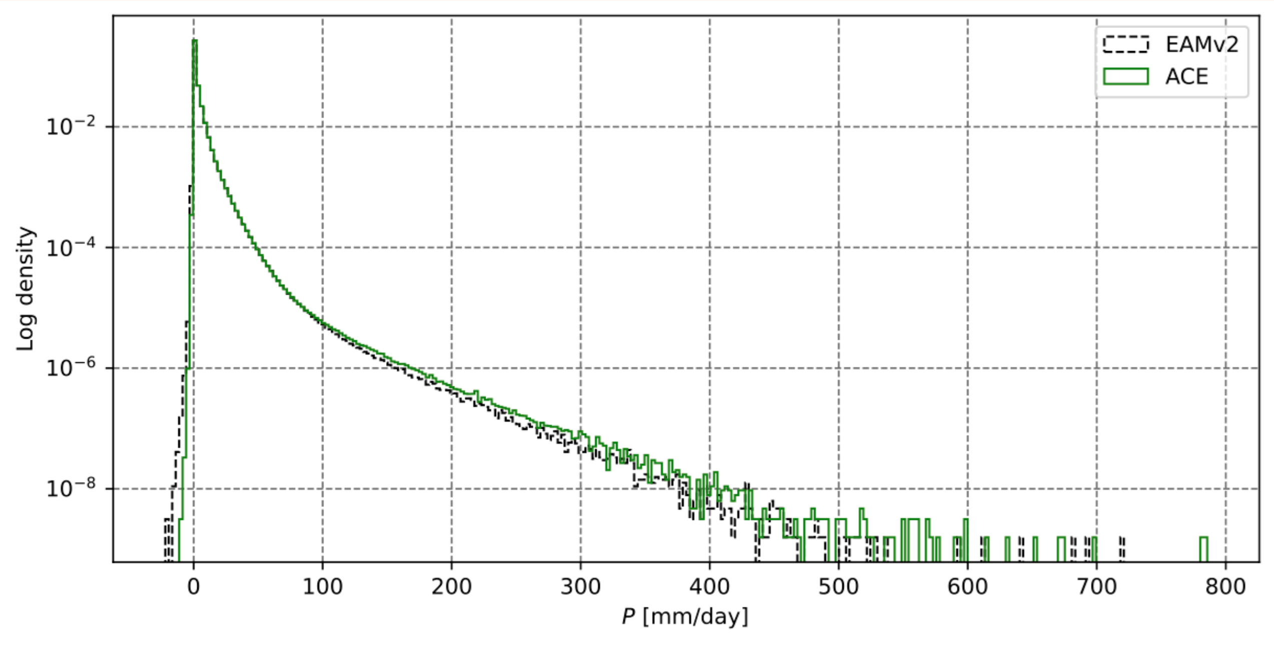


ACE outperforms the 2x-coarser baseline on 90% of the output variables
(time-mean pattern RMSE)

Watt-Meyer et al. (2023)

Not unique to FV3: Emulating DOE EAMv2 with ACE

Daily precipitation PDF over all grid points



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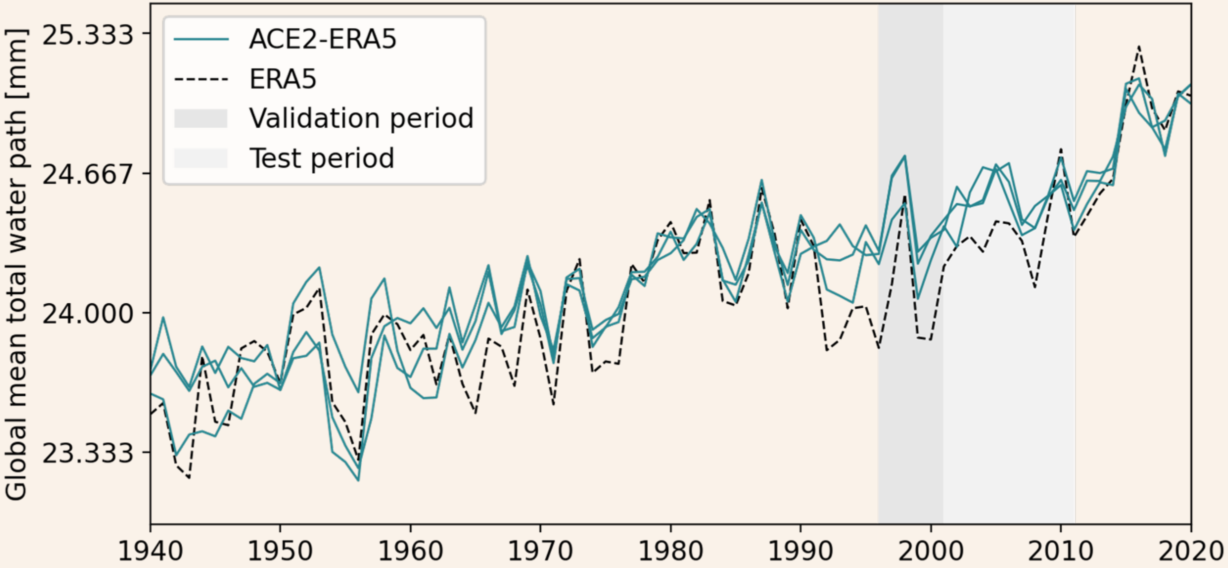
Duncan et al. (2024)

ACE2

- Built-in dry air and moisture conservation, CO_2 added as an forcing
- Architectural improvements in capacity, loss function, normalization
- Trained and tested on AMIP (historical SST variability) with ERA5 or SHiELD
- 1500 simulated years per day on an H100 GPU

Watt-Meyer et al. 2024, http://arxiv.org/abs/2411.11268, submitted to *NPG Climate & Atm Sci*

ACE2-ERA5 emulates historical climate given observed ocean temperatures and CO_2 trends.



- Water vapor path: a proxy for global water cycle
- The three ACE lines sample random weather variability
- Even wiggles due to El Nino are well captured by ACE

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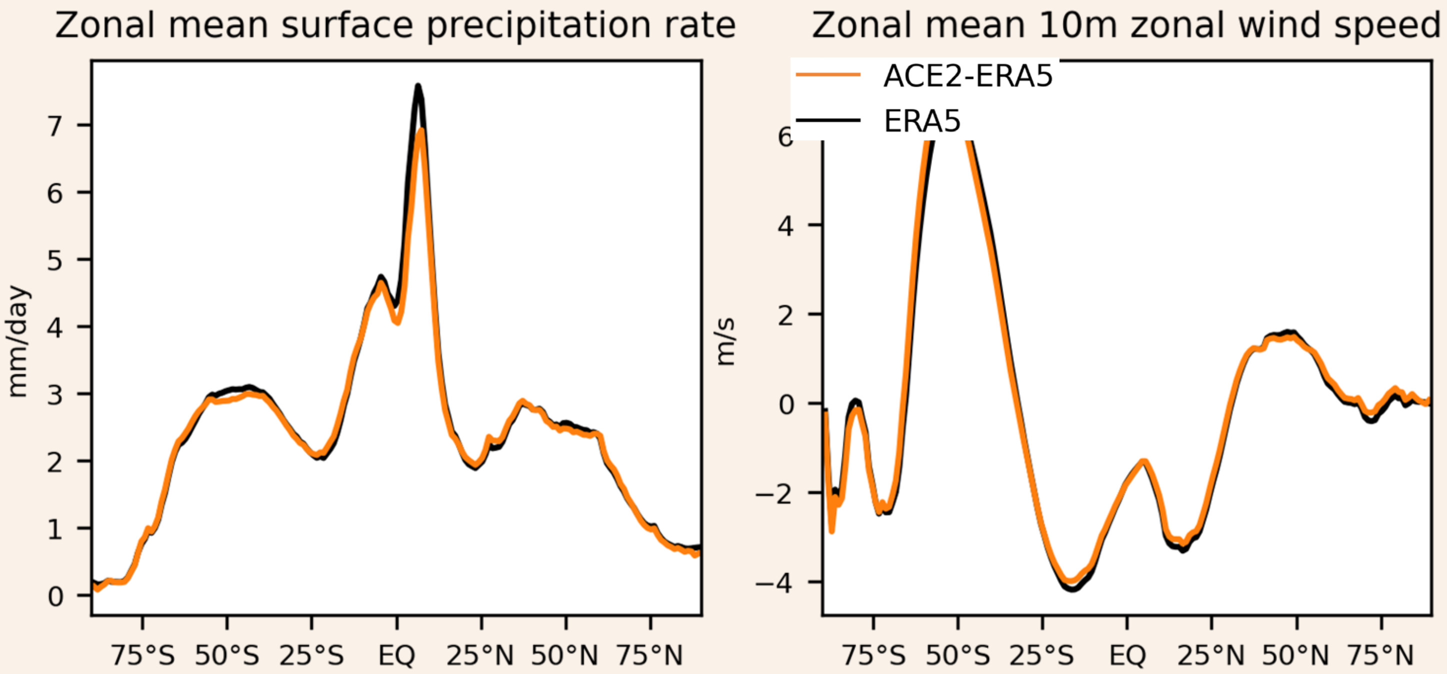
Watt-Meyer et al. 2024

Highly accurate climatology



2001-2010
test period

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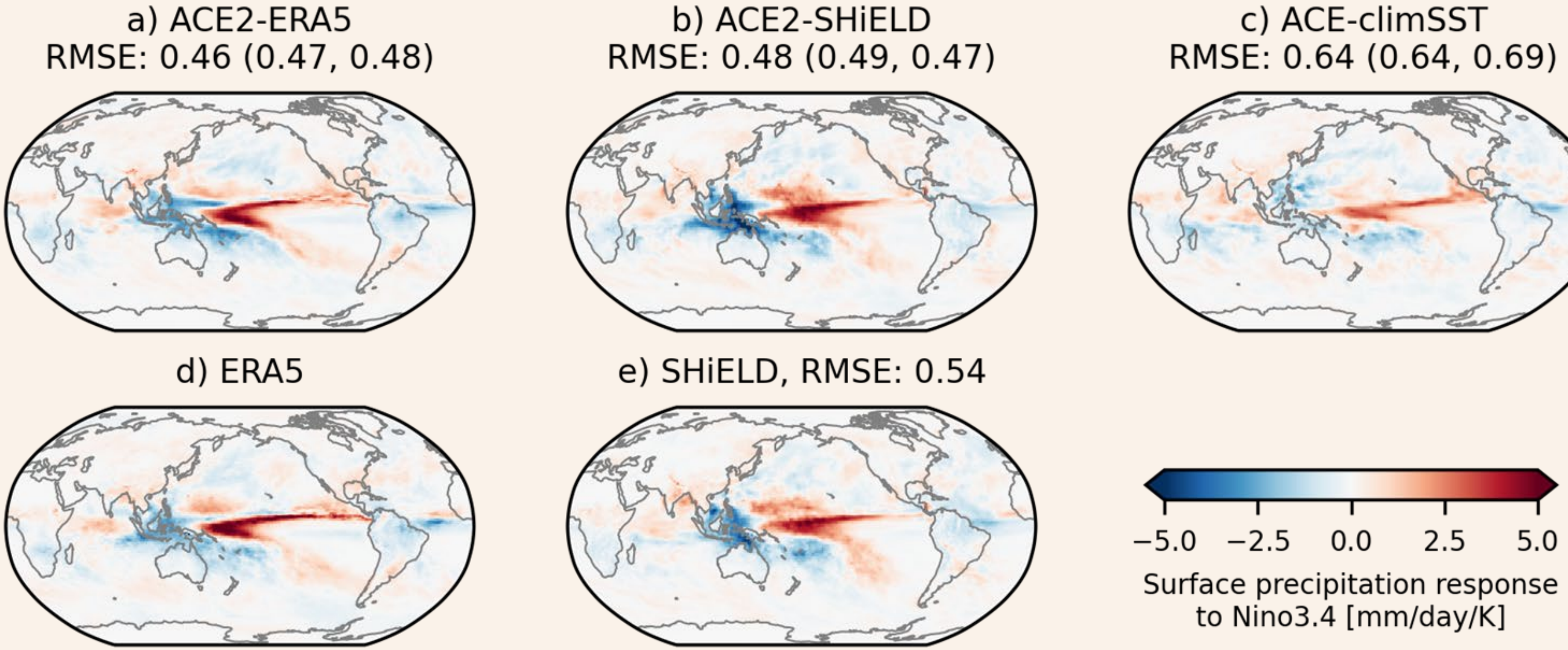
Watt -Meyer et al. 2024

ACE2 responds accurately to El Niño SST variability



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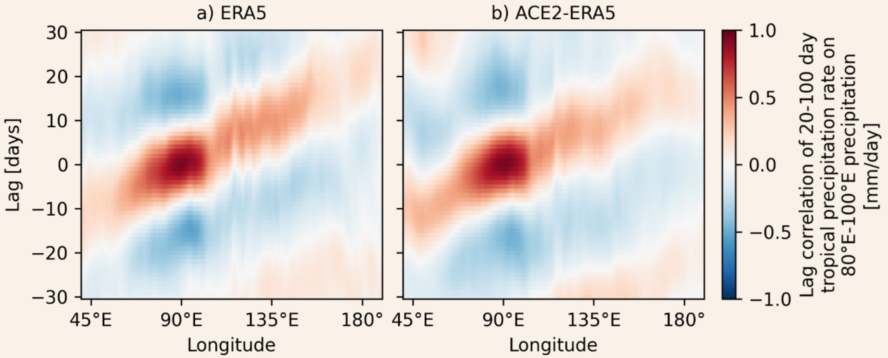
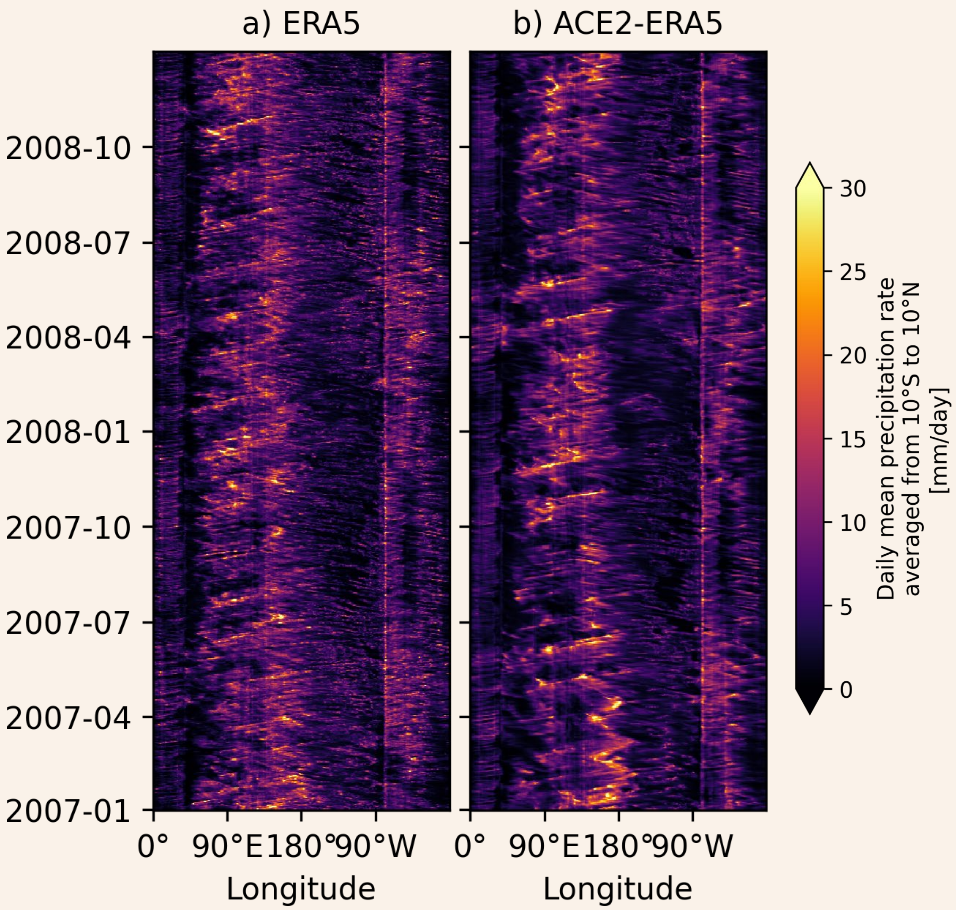
Watt -Meyer et al. 2024

Based on 2001-2010 period

ACE2 tropical precip variability

..also does a good job with tropical cyclone climatology and stratospheric sudden warmings





Watt-Meyer et al. 2024

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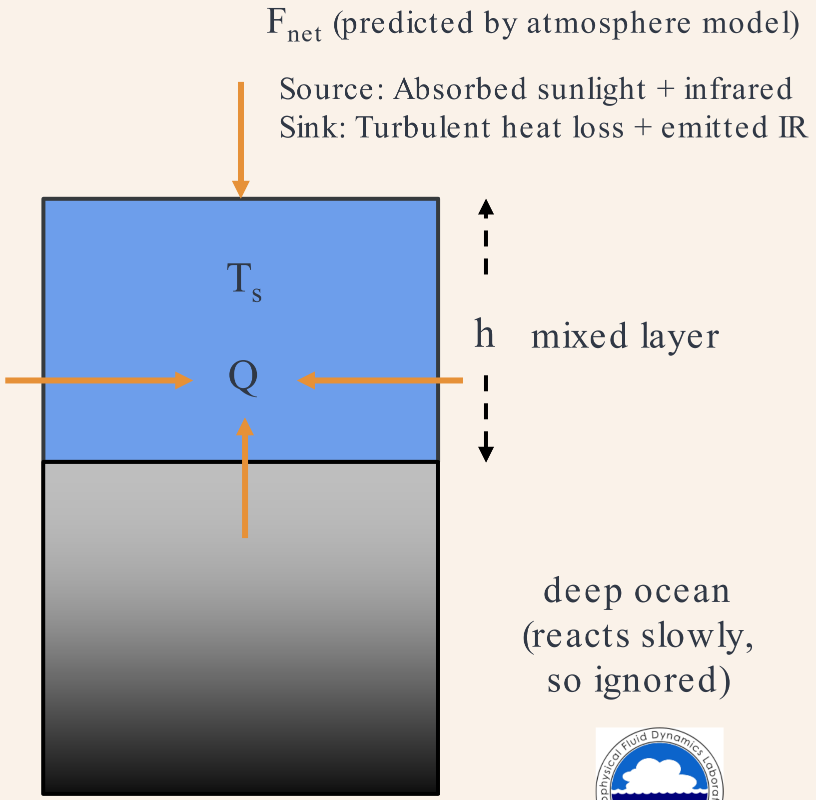
ACE2 + interactive slab ocean (ACE2-SOM)

- Generate training/validation data from three 50-year simulations:
    - $1xCO_2$
    - $2xCO_2$
    - $4xCO_2$
- Train ACE-SOM with CO_2 as an input.



Clark et al. 2024, https://doi.org/10.48550/arXiv.2412.04418, submitted to *JGR-ML*

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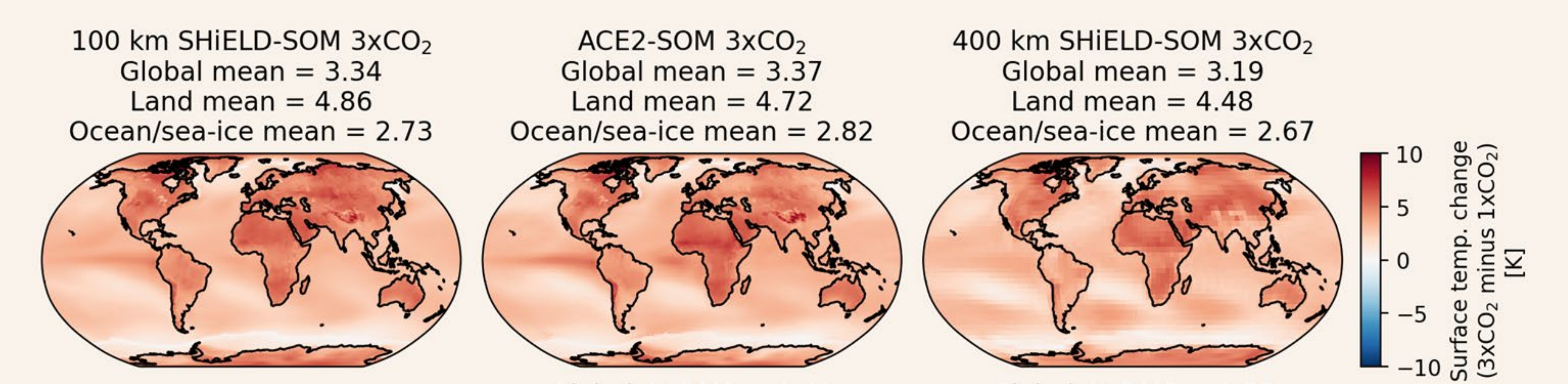
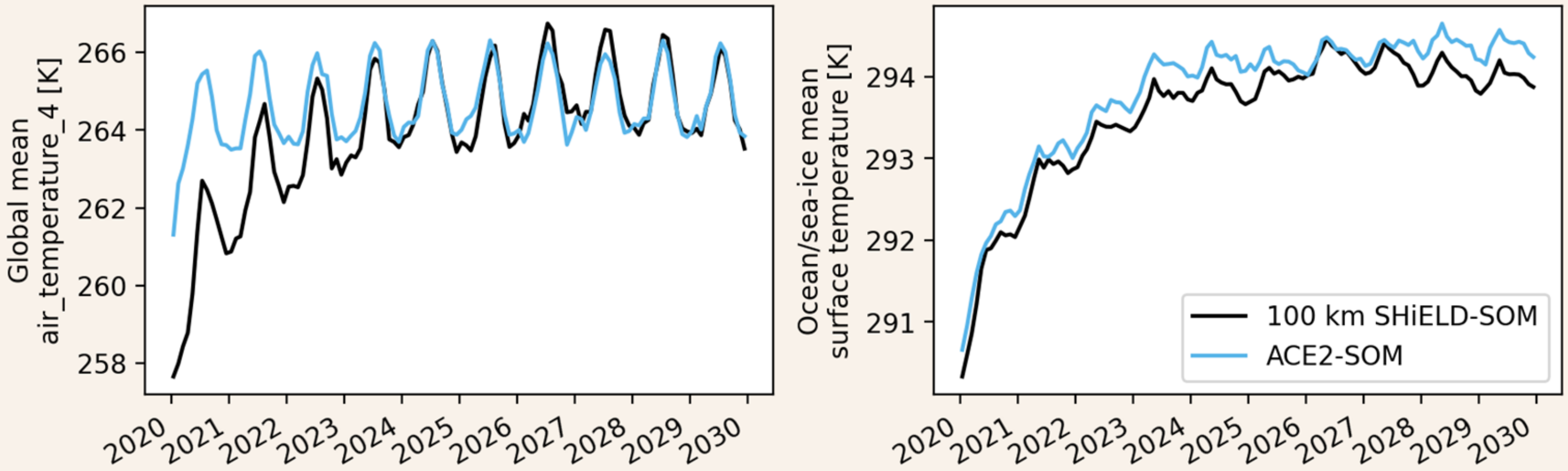
ACE2-SOM is stable and accurate in multiple climates



ACE2-SOM global warming pattern matches the physics-based model, capturing robust features like amplified warming over land.

Clark et al. 2024

Out of sample test: Abrupt $4xCO_2$ increase



- ML-controlled fields (except ocean temperature) unrealistically jump to $4xCO_2$ regime.
- Ocean temperature, aided by prescribed thermal inertia, warms realistically slowly.
- ACE2-SOM still finds the right steady state, helped by its equilibrium $4xCO_2$ training.

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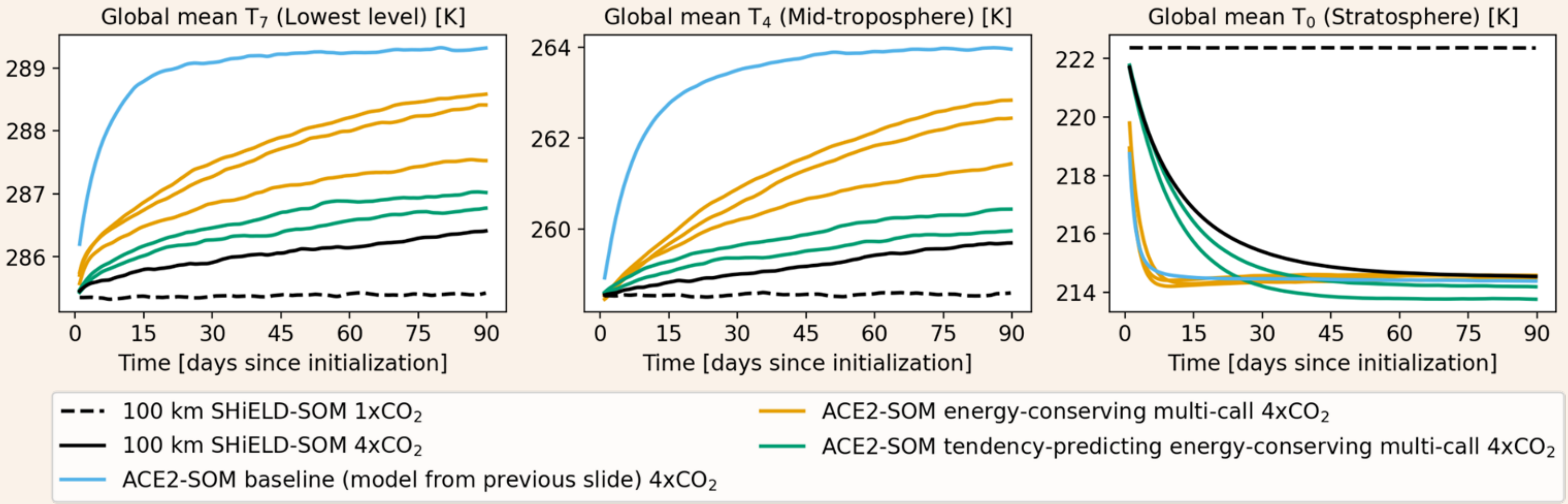
Clark et al. 2024

Physics-informed advances to ACE2 fix abrupt 4xCO_2

- Global energy conservation built into ML
- Radiative fluxes calibrated to learn correct sensitivities to changed CO_2
- Learn tendencies, not state updates
- Train on a 70 year 2%/year CO_2 rise reference SHiELD-SOM run



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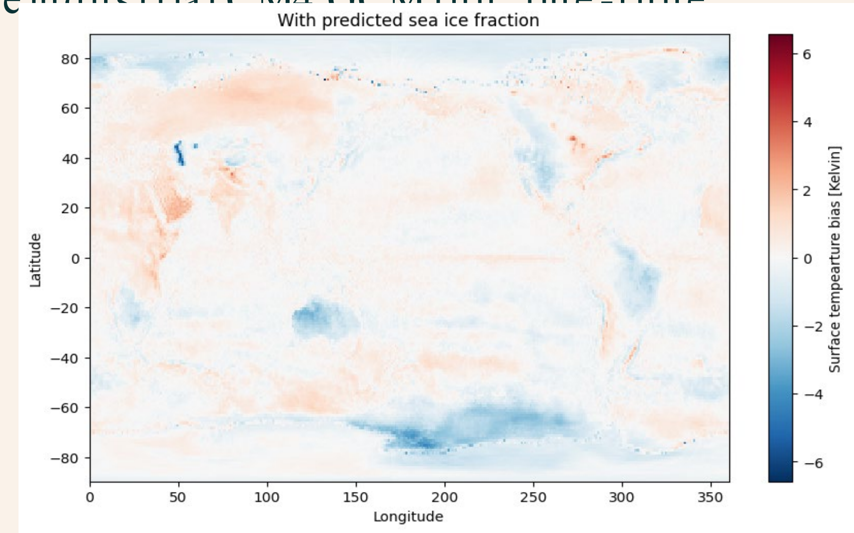
Coupled emulator (ACE + M^2LInES Samudra)

- Samudra ocean emulator: 19 layers spanning ocean depth, 1° resolution, 5 day time-step
- Coupled to ACE via 5-day mean ACE-predicted surface fluxes
- Interactive learned sea-ice
- Train uncoupled emulators on 160 years of preindustrial CM4 GCM run; fine-tune coupled
- Test on 40 remaining years of this run
- Inference is stable, without climate drift
- Modest TS and ocean heat uptake biases



Samudra: *Djeeshjith et al. 2024 arXiv*

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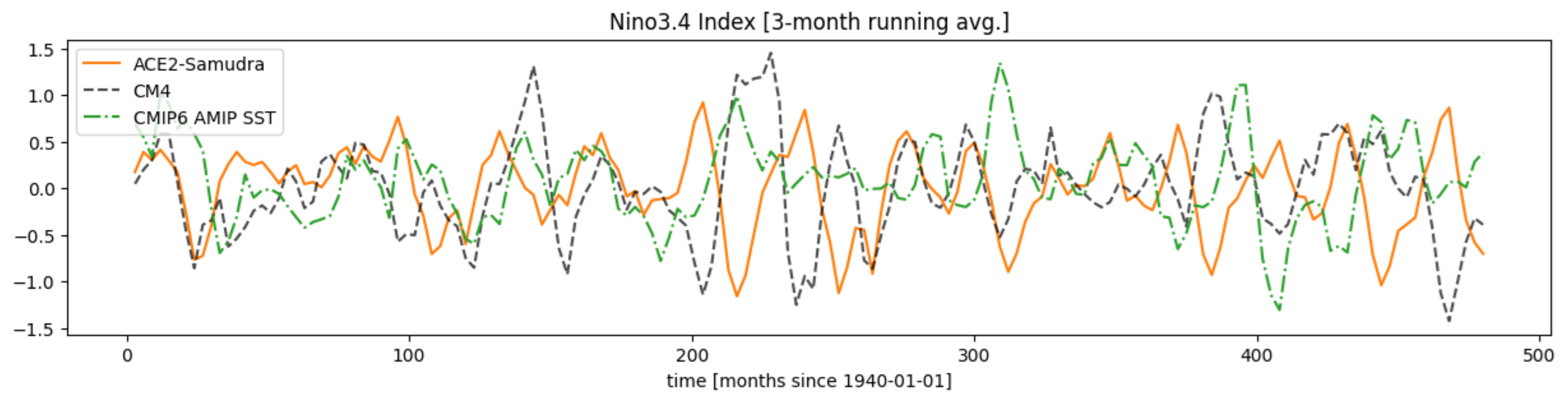
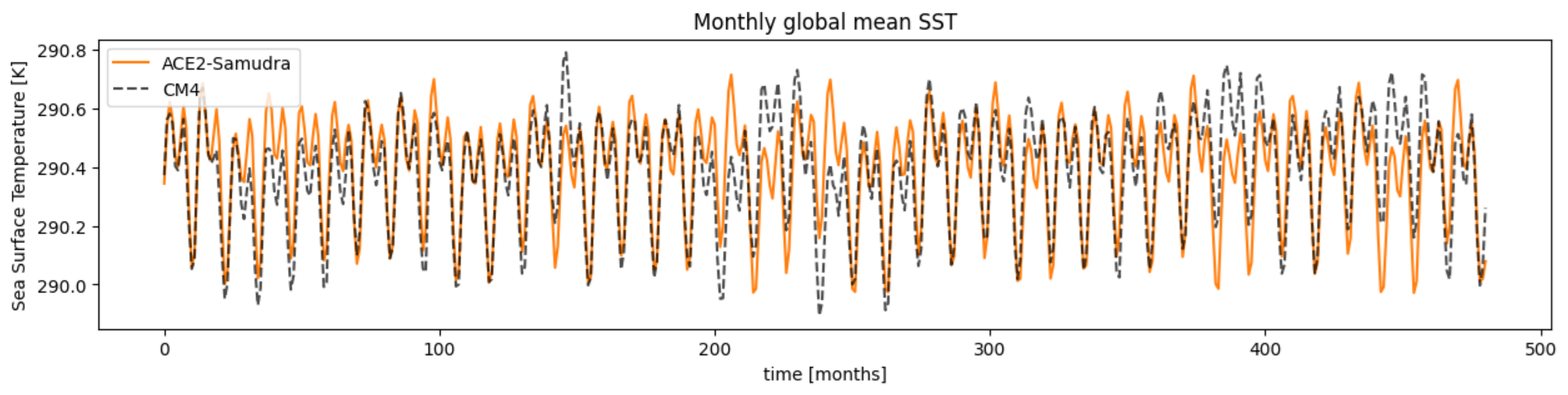
ACE2-Samudra Coupled SST and Nino3.4 index

Coupled emulator shows Nino3.4 variability comparable to the ground truth CM4 simulation (and obs).





[wandb]

Summary

ACE

- The Ai2 Climate Emulator (ACE) is a stable, accurate ML-based atmospheric model that is nearing suitability for climate prediction
- Faithfully reproduces reference model's climate
  - Skillful in climSST, AMIP, and slab-ocean/perturbed CO_2 configurations
  - Captures forced response to GHG and ocean-atm variability (ENSO)
- Easier and 1000x faster to run than the reference model!
- Ongoing work
  - Energy conservation & accurate ML of CO_2 effects on radiative heating
  - Coupling to an emulator of a dynamical ocean model

Open-source code, data and model checkpoints: github.com/ai2cm/ace

ACE: Watt-Meyer et al. 2023; Duncan et al. 2024; ACE2: Watt-Meyer et al. 2024; ACE2-SOM: Clark et al. 2024