AI for Climate Modeling: Present and Future

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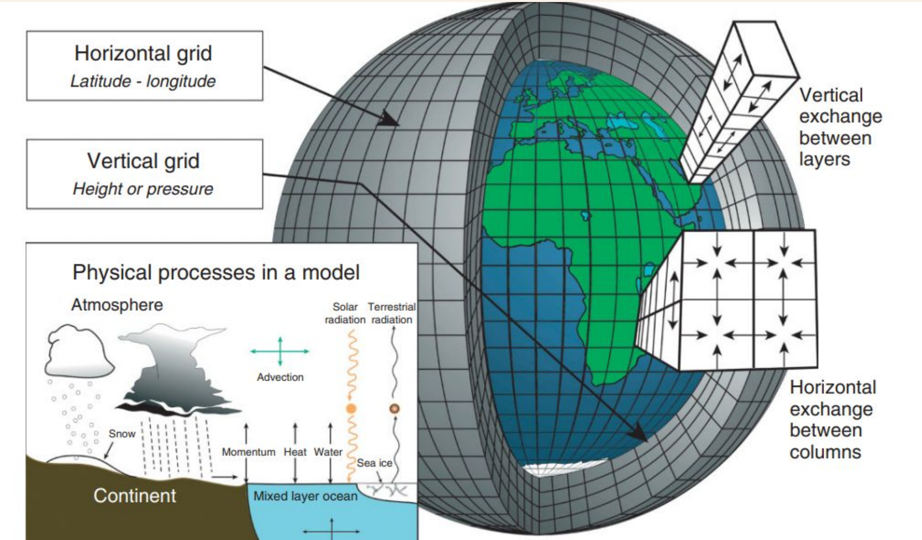
External partners

M²LInES GFDL LLNL NVIDIA

Physically based weather and climate modeling

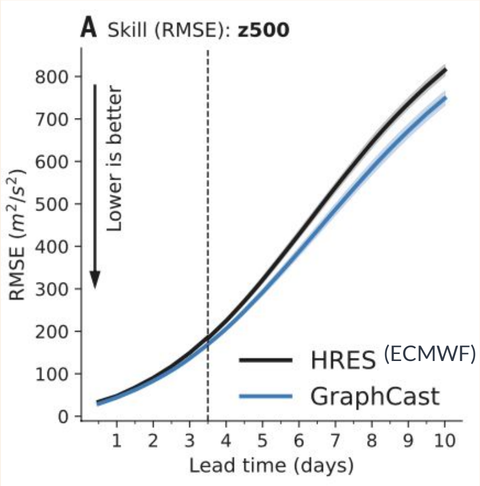
- Modular components
- Physically/empirically based
- Designed to generalize across climates
- Climate simulated as statistics of weather interacting with ocean, land, ice
- Enables ‘seamless prediction’
- Analogous to ML foundation models (can fine-tune for many applications)



Edwards, P. N. (2011)

ML-based weather forecasts are state of the art

- Trained on global reanalyses (e.g. ERA5)
- Improved 1-10 day forecasts in seconds
- Skillful ML seasonal forecasts (ORCA, FuXi,...)
- **Seamlessly extend to climate, like GCMs?**



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

Global atmospheric state (>1M variables) → Encoder → Horizontal exchange ↕ Grid-column processing → Decoder → State 6-24 hours later

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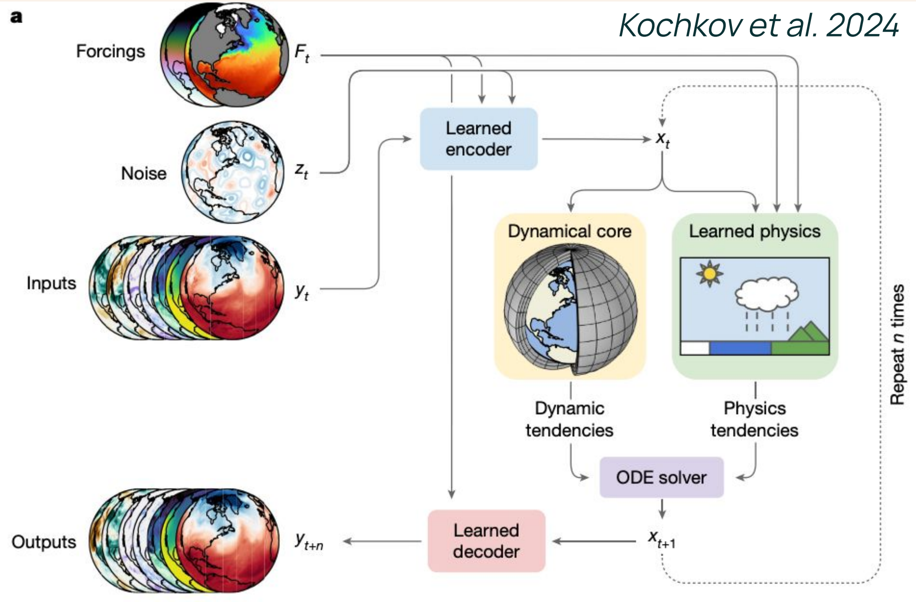
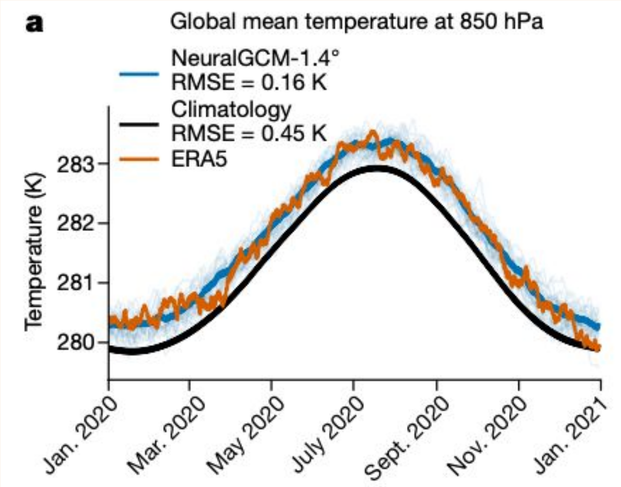
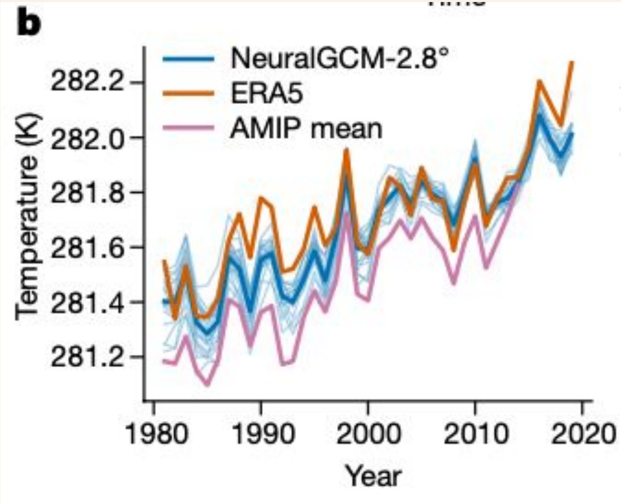
Stretching toward climate AI

- Most AI weather models are not stable or realistic past a month or two (but a few are…)
- Seasonal and ENSO forecasts must include upper ocean evolution, but not full-depth ocean
- AI modeling challenges for decadal and longer climate simulation:
  - For most purposes, must couple atmosphere, land, ocean, sea ice, etc.
  - Generalizability across the past and foreseeable future range of climates
    - Forced response to SST, GHGs, aerosols, etc.
  - Accurately simulate coupled atmosphere-ocean variability and long-term trends
- Strategies
  - Architectures
    - Hybrid: ML replaces/corrects parts of the atmospheric model
    - Full model replacement: ML of entire global atmospheric evolution
  - Training
    - Model emulation: ML of evolution of a physics-based global atmosphere model
    - Historical emulation: ML trained on historical global reanalysis
  -

NeuralGCM - a hybrid AGCM





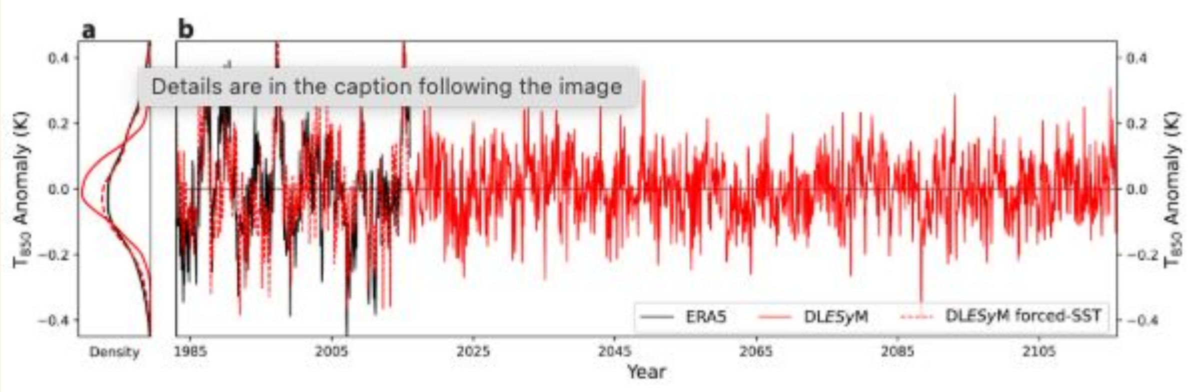


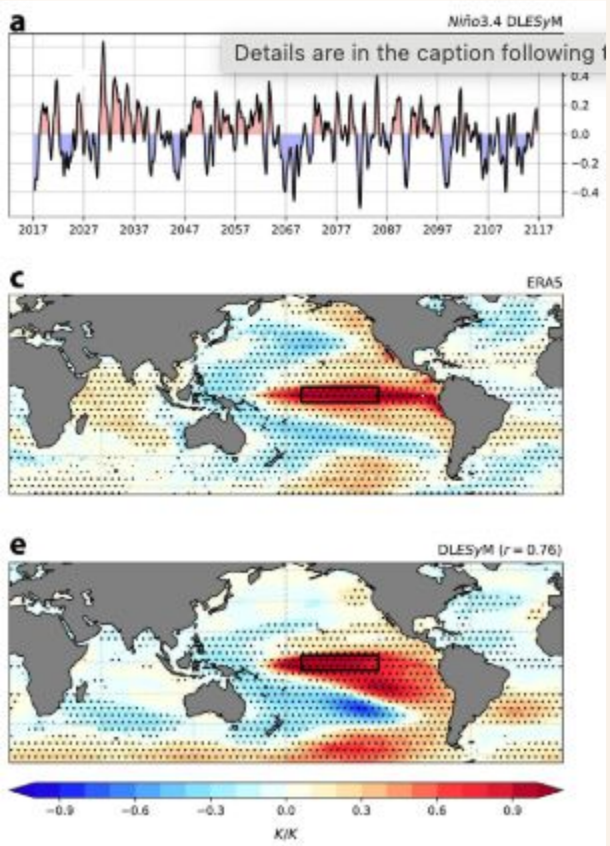
Hybrid architecture developed by Google Research

- Spectral dynamical core coded in Jax enables ML differentiability
- ‘Column-local’ physics machine-learned to optimize forecast wrt ERA5
- Accurate weather forecasts and 1980-2020 SST-forced climate change

DLESyM - historical emulation

- Full model replacement using U-Net with ConvNext blocks
- Developed by Durran group at University of Washington
- Evolved from DLWP AI weather model (*Weyn et al 2021*)
- Trained on ERA5
- Includes coupling to a simple upper ocean representation
- Stable, accurate repeating seasonal cycle in current climate
- Weak ENSO variability

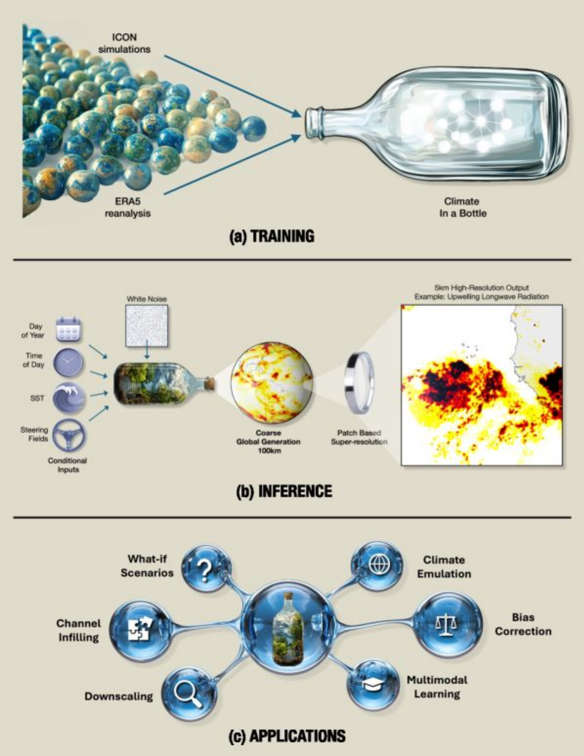


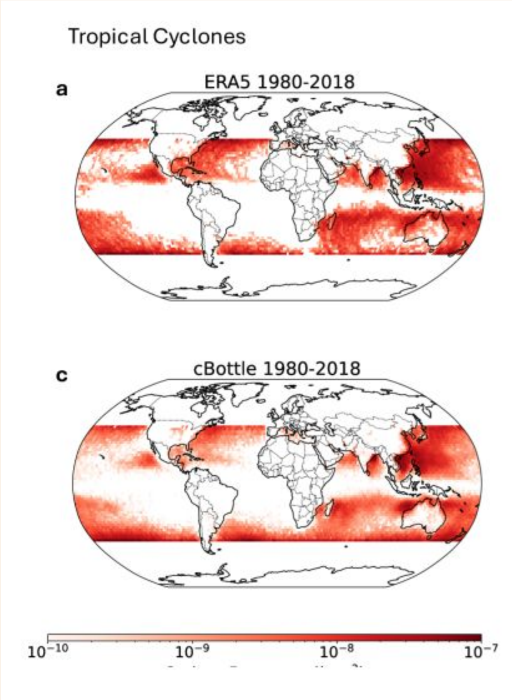


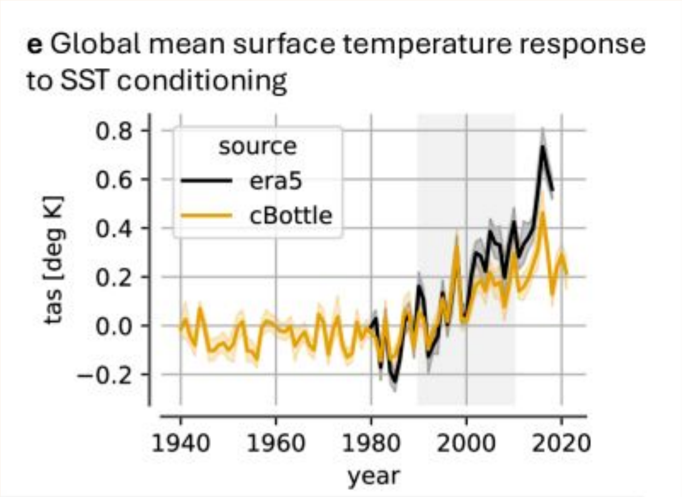
Cresswell-Clay et al. 2025

cBottle - fast probabilistic sampling of historical climate

- NVIDIA generative conditional sampler of ERA5 with ICON-based global km-scale downscaling







Trend accurate, but only during ERA5 training sample!

Sampling ≠ sequential rollout

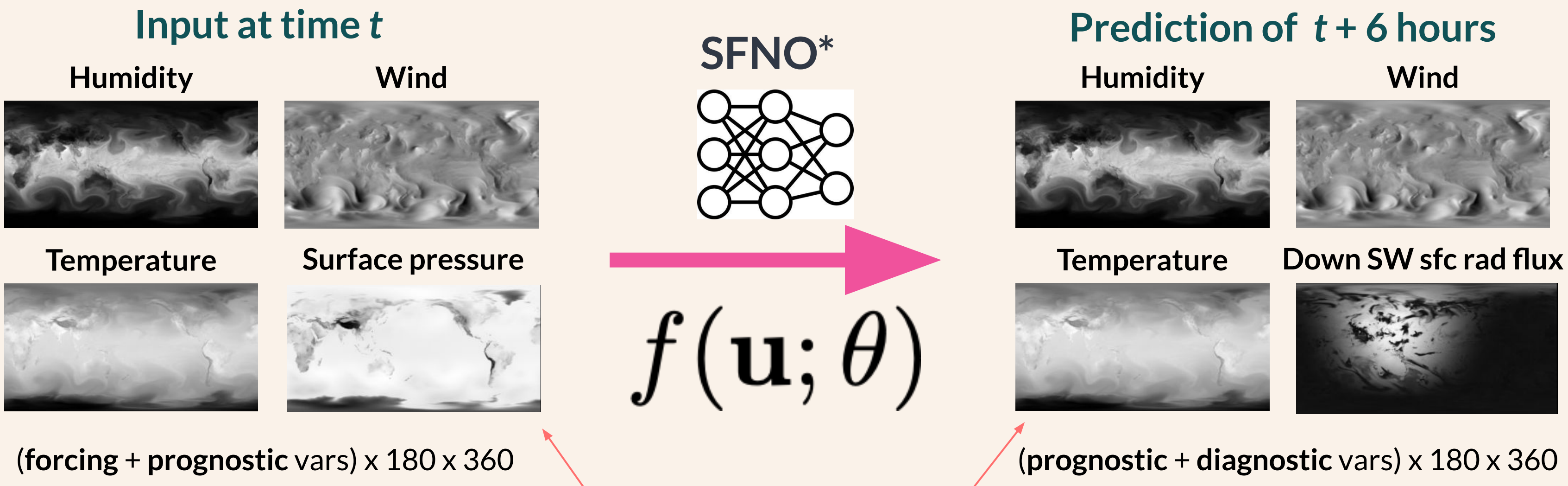
Brenowitz et al. 2025, https://arxiv.org/html/2505.06474v2

Ai2 Climate Emulator (ACE) - historical & model emulation

- 'Seamlessly' derive climate as statistics of weather, like physics-based GCMs
- Train on climate model output, not just historical reanalysis
  - **Diverse range of climates** (global warming, paleoclimate etc.)
  - **Rigorous testing of generalizability** to unseen climate scenarios
- Start simple, then increase complexity:
  - 100 km grid; predict 8 atmospheric layers + boundary energy and moisture fluxes
  - ACE1: **annually-repeating** ocean temps, fixed human forcing
  - ACE2: **more realism** - historical forcings, CO_2 increase, ocean coupling

Training Setup

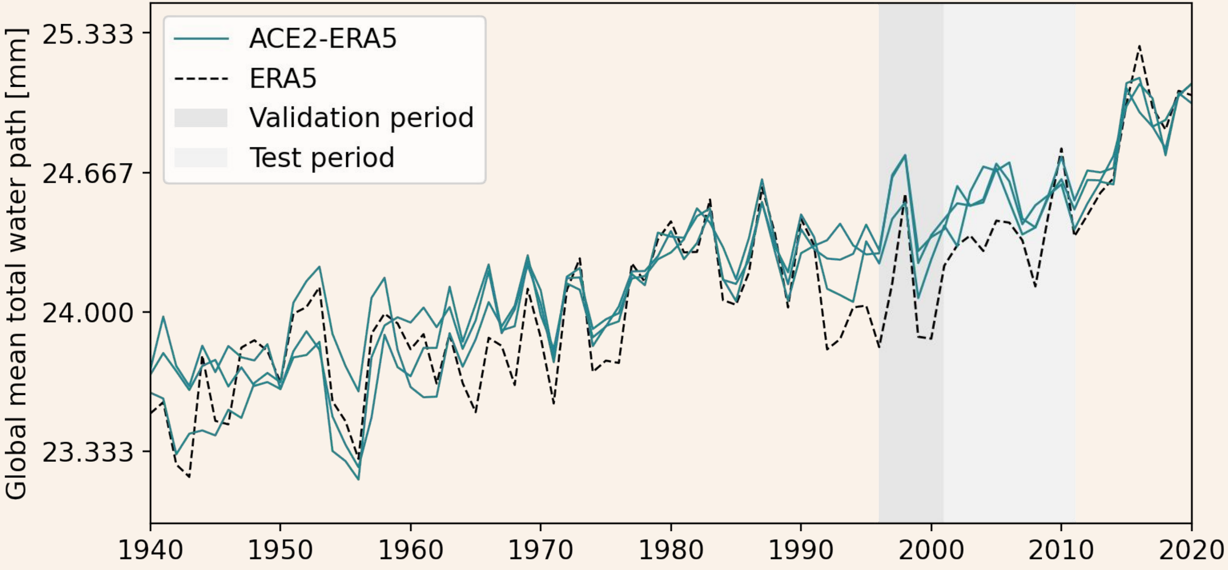
Loss function: mean-squared error of 6-hour forecast computed over all the output variables (for ACE2, accumulated over 2 forward steps)



Showing subset of inputs/outputs

***SFNO**: Spherical Fourier Neural Operator (*Bonev et al., 2023*)

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
- Seamless emulation of weather and atmospheric component of climate

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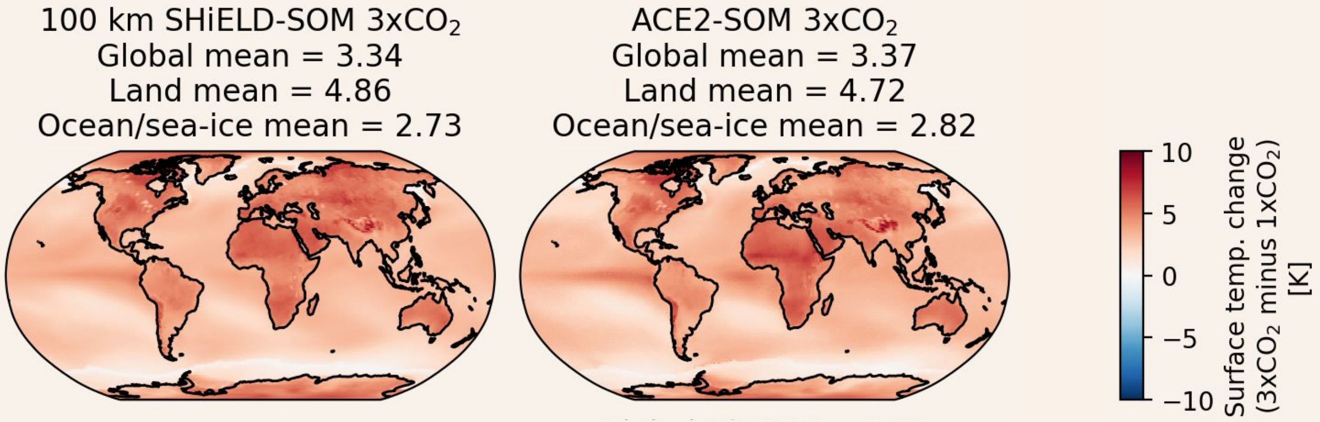
Watt-Meyer et al. 2025, npj Climate & Atm. Sci.

ACE2-SOM is stable and accurate in multiple climates



- SOM = slab ocean model, coupled to either reference physics-based AGCM or ACE2
- Train 6hr ACE2-SOM forecasts with AGCM sims in 1xCO_2, 2xCO_2, 4xCO_2 climates
- Test on 3xCO_2 - 1xCO_2 climate change
- ACE2-SOM global warming pattern closely matches AGCM

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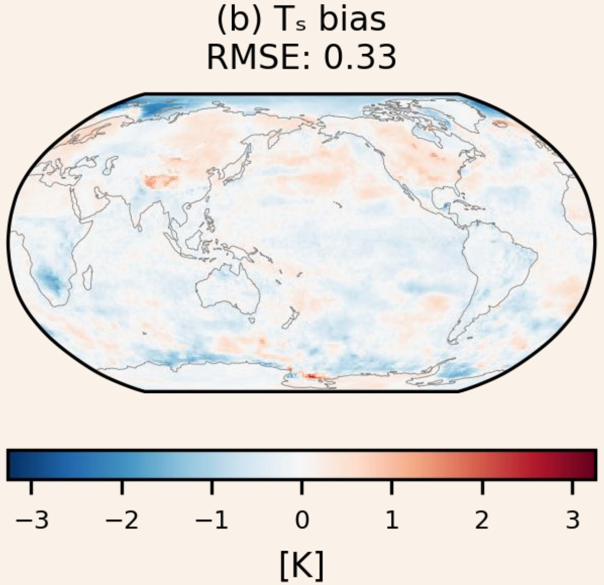
Clark et al. 2025, GRL

SamudrACE coupled emulator (ACE + M^{2}LInES Samudra)

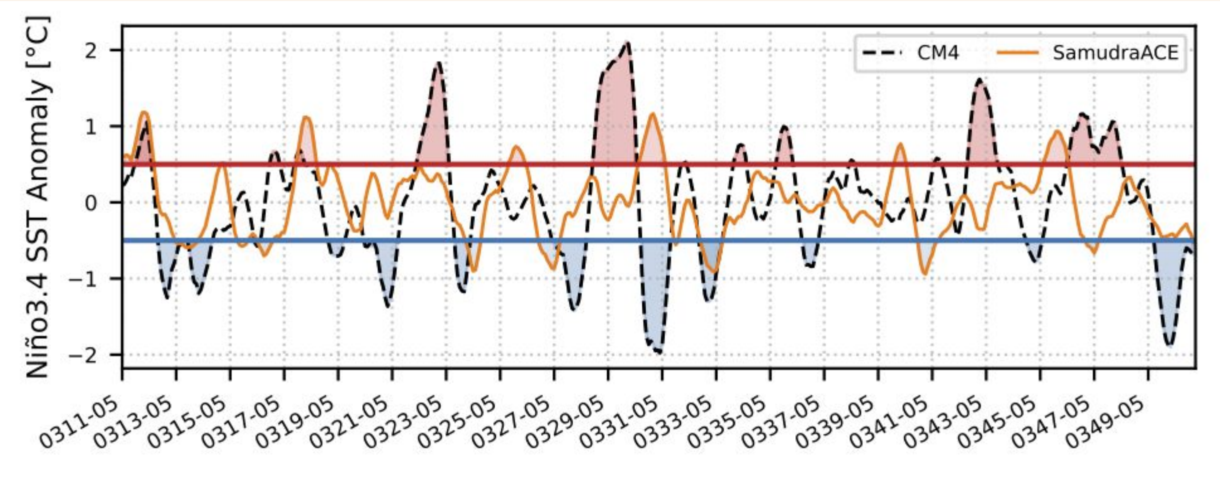
- Samudra ocean emulator: 19 layers spanning ocean depth, 1° resolution, 5 day time-step
- Coupled to ACE2 via 5-day mean ACE-predicted surface fluxes
- Interactive learned sea-ice (Ai2)
- Train uncoupled emulators on 160 years of preindustrial CM4 GCM run; fine-tune coupled
- Test on 40 remaining years of this run
- Inference is stable, without climate drift
- Demonstrates coupling of modular ML emulators



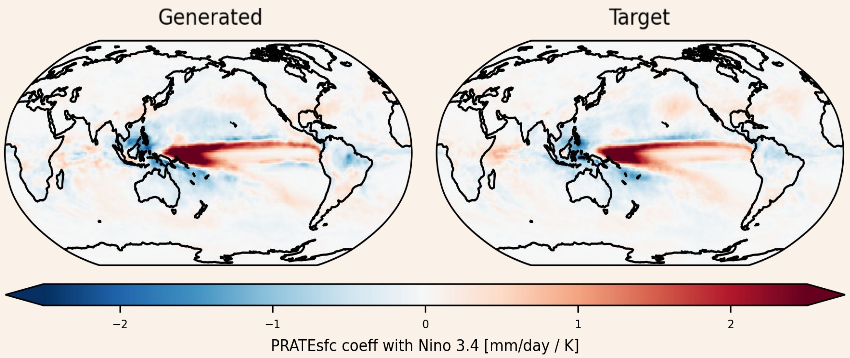
Samudra: *Dheeshjith et al. 2025 GRL*
ACE+Samudra coupling: *Duncan et al. 2025 arXiv, submitted to GRL*

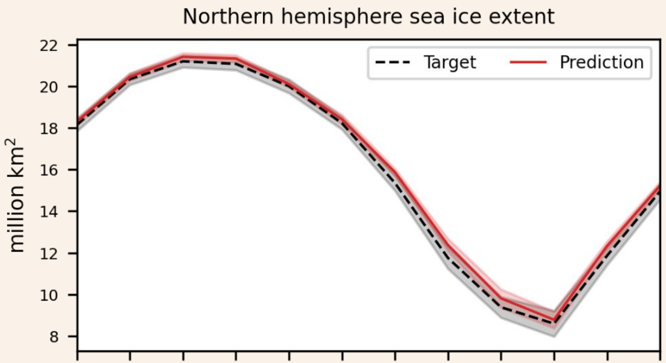
ACE2-Samudra Nino3.4 index and NH sea ice extent

Nino3.4 variability and SST annual cycle over 40-year test period are comparable to the reference CM4 simulation



d) Precipitation response to ENSO conditions





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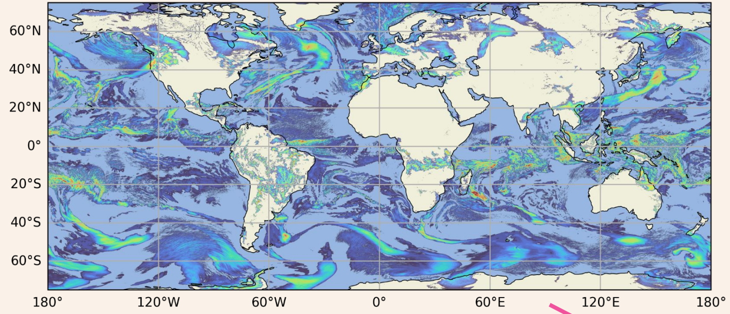
Duncan et al. 2025

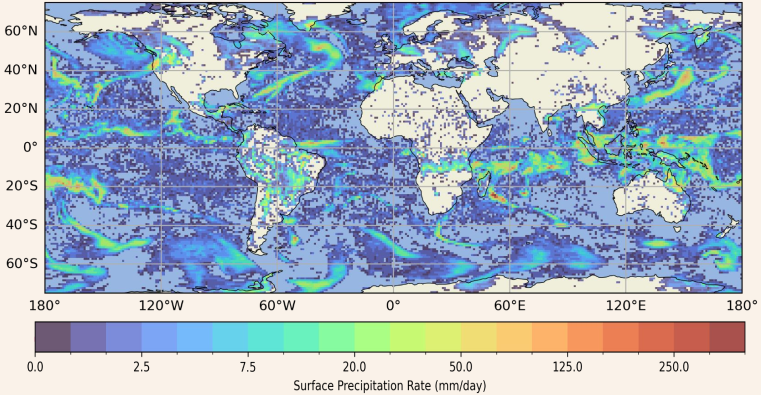
AI emulation & downscaling of km-scale atmosphere model

10 yr 3 km GFDL X-SHiELD simulation

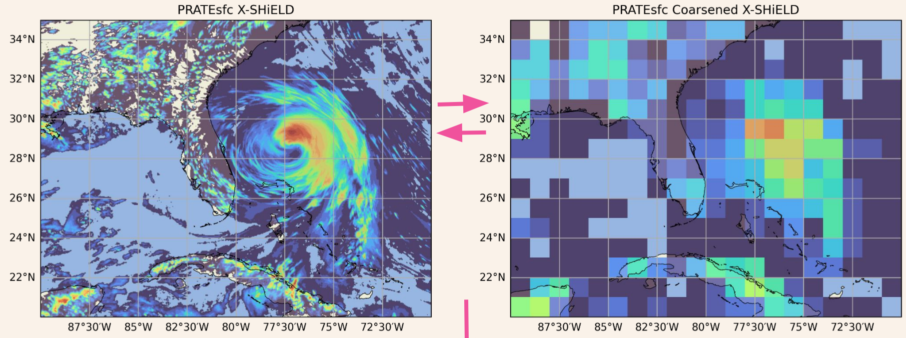


Coarsen to 100 km

Train stochastic version of ACE2

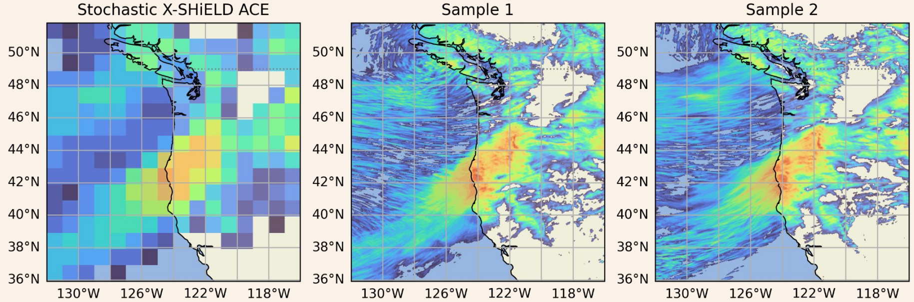


Globally-trained CorrDiff AI patchwise downscaling 100 → 3 km



Generate 3 km downscaled patches from ACE and a single CorrDiff downscaling model anywhere and for any time period.

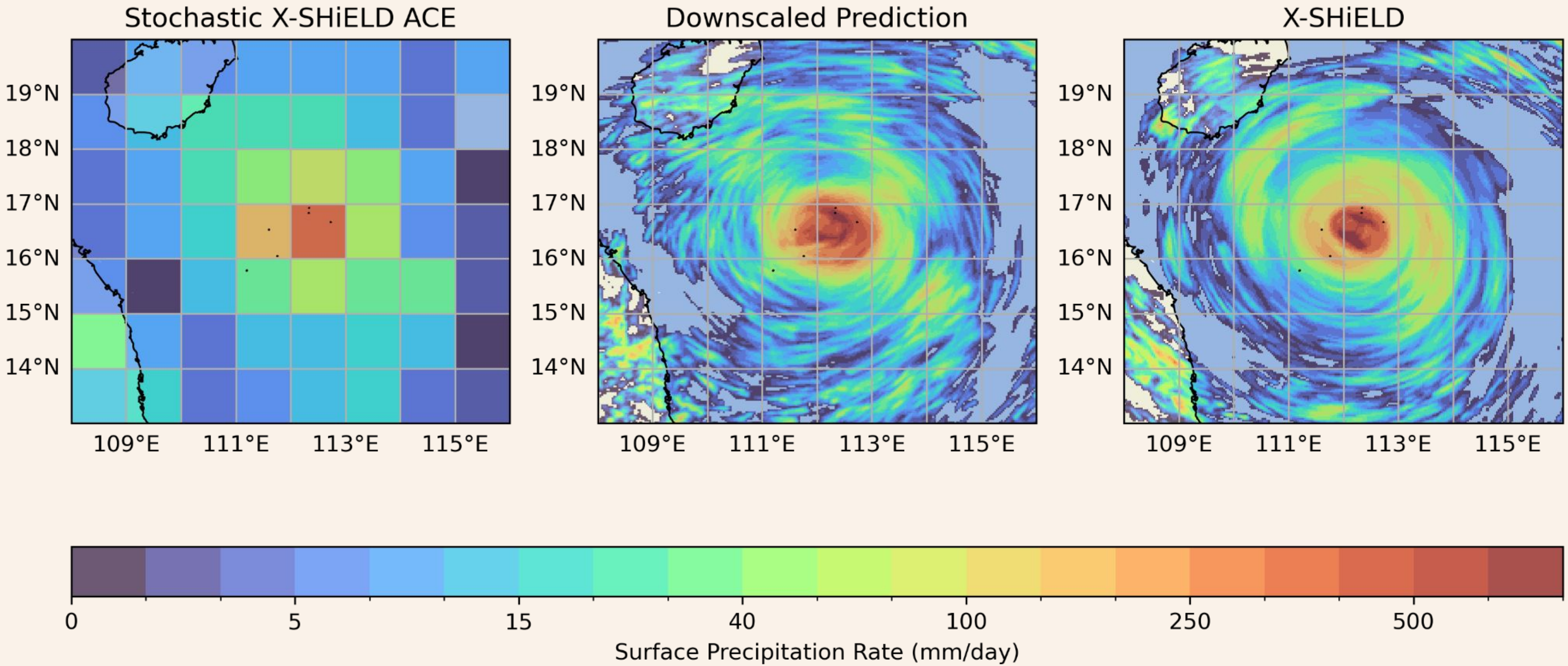
ACE



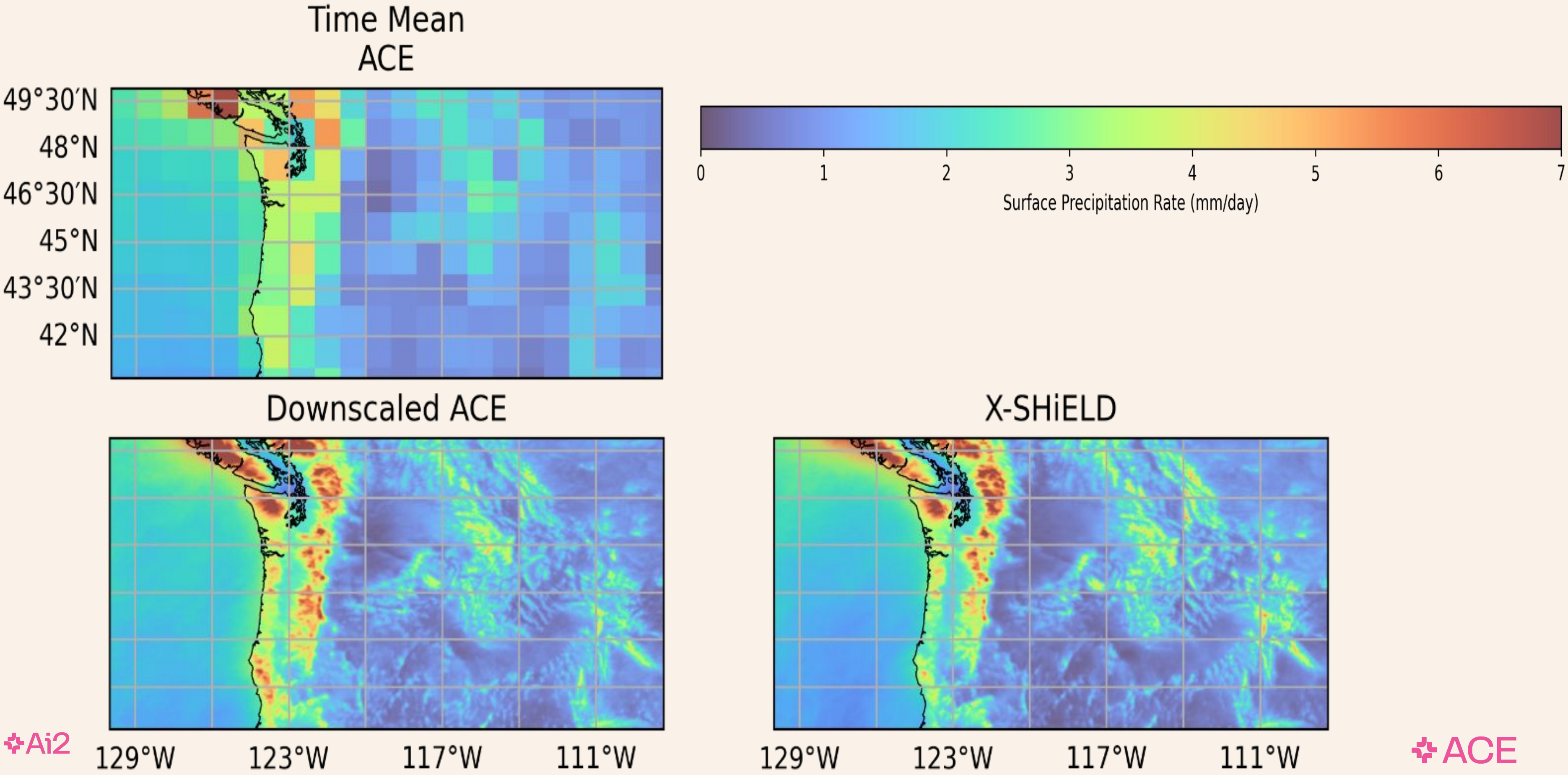
Publication in prep.

ACE

TC simulated by ACE at 100 km and downscaled to 3 km



ACE downscaling reproduces km-scale annual mean precipitation



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ACE

Summary

- AI-based climate models will soon be ready to accelerate some routine and computationally intensive climate modeling tasks (large ensembles, downscaling)
    - Could 'democratize' climate modeling: 100x faster, easier to use
    - For multi-decade projection, must train AI to emulate physically-based models
- Research grand challenge: Develop AI models trained on historical observations alone that can convincingly generalize to future climates better than physics-based models
    - Learn 'climate-invariant' representations of uncertain physical processes? (Pierre)
    - AI is challenged by process diversity and range of earth system time/space scales
    - AI models are poorly suited for projecting climate 'tipping points'
- Physics-based and AI modeling have complementary strengths and work best together