Improving climate models using corrective machine learning

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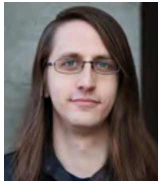

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Webpage: https://allenai.org/climate-modeling

AI2 Climate Modeling ML group

Philanthropic project of the Allen estate, at Vulcan (2019-2021) and now at AI2.

- Goal: Halve climate model uncertainty about 21C regional precipitation trends
- Strategy: Make coarse-grid climate models better using fine-grid models as reference

Partnered with NOAA/GFDL, developers of a 3-km version of FV3GFS global weather model

Ongoing collaborations with other R&D groups (e.g. NVIDIA, LLNL) and summer interns

How can ML help weather and climate models?

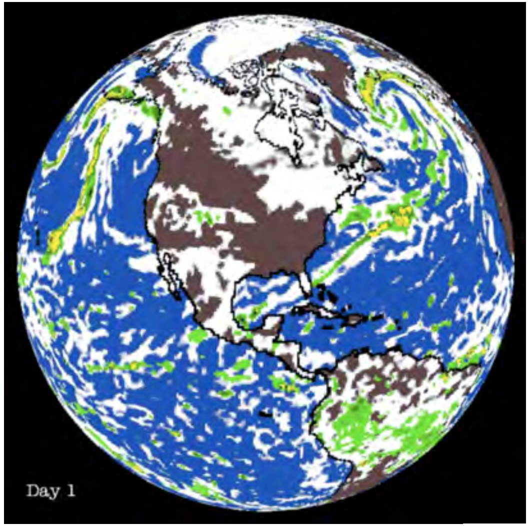
Make global weather and climate models:

- accurate
- faster
- affordable

Three general strategies:

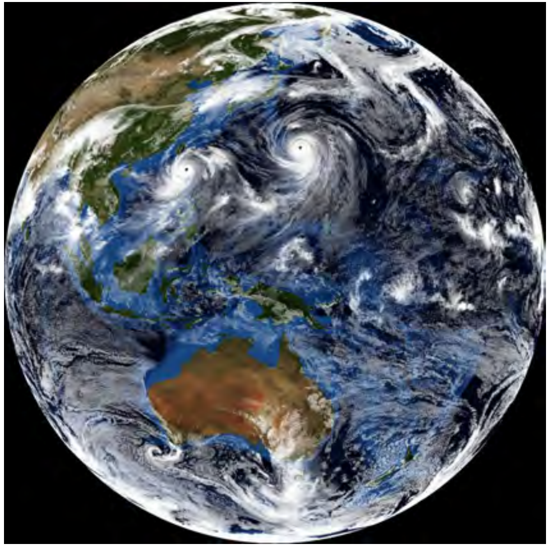
- Hybrid: Replace or correct parts of the climate model, e.g. physics parameterizations
- Full model emulation (FME): ML of entire global atmospheric evolution
- Flexible, nonlinear bias correction

Corrective ML to improve coarse-model simulations

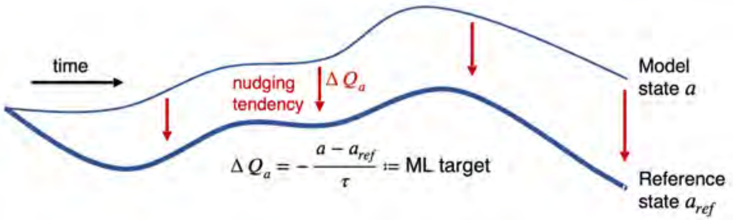


Climate model (25-200 km)

Train corrective ML to make temperature, humidity, winds of the coarse model track reference data.

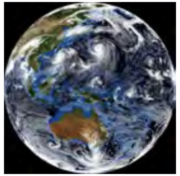


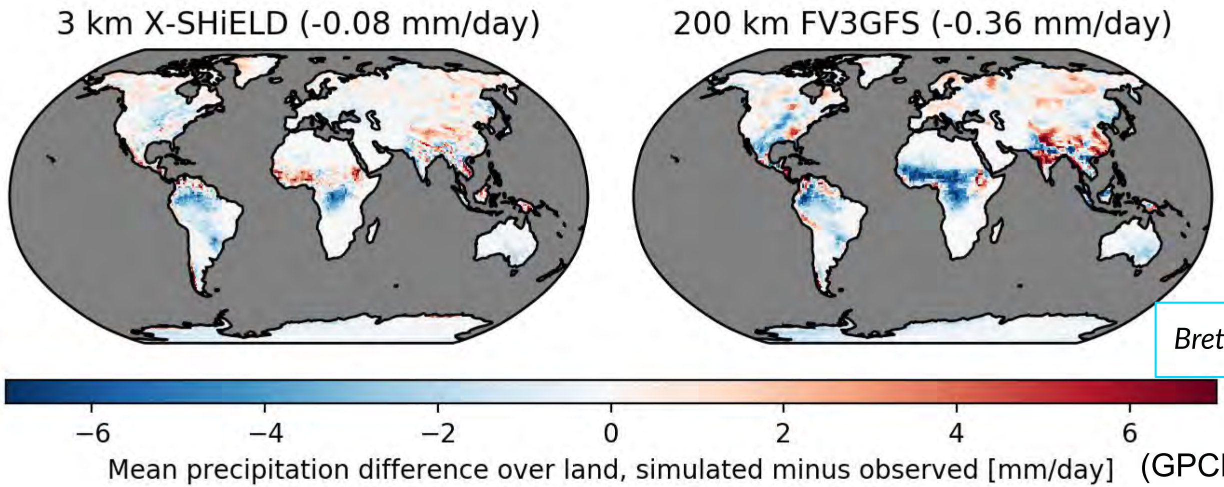
High fidelity reference: observations or fine-grid (3 km) simulation



3-hrly nudging tendencies are interpreted as a needed correction to the physical parameterizations and coarse-grid dynamics

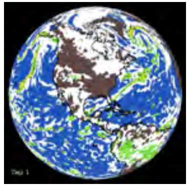
Fine-grid reference model:
accurate simulations across a range of climates





(GPCP)

Bretherton et al. 2022, JAMES

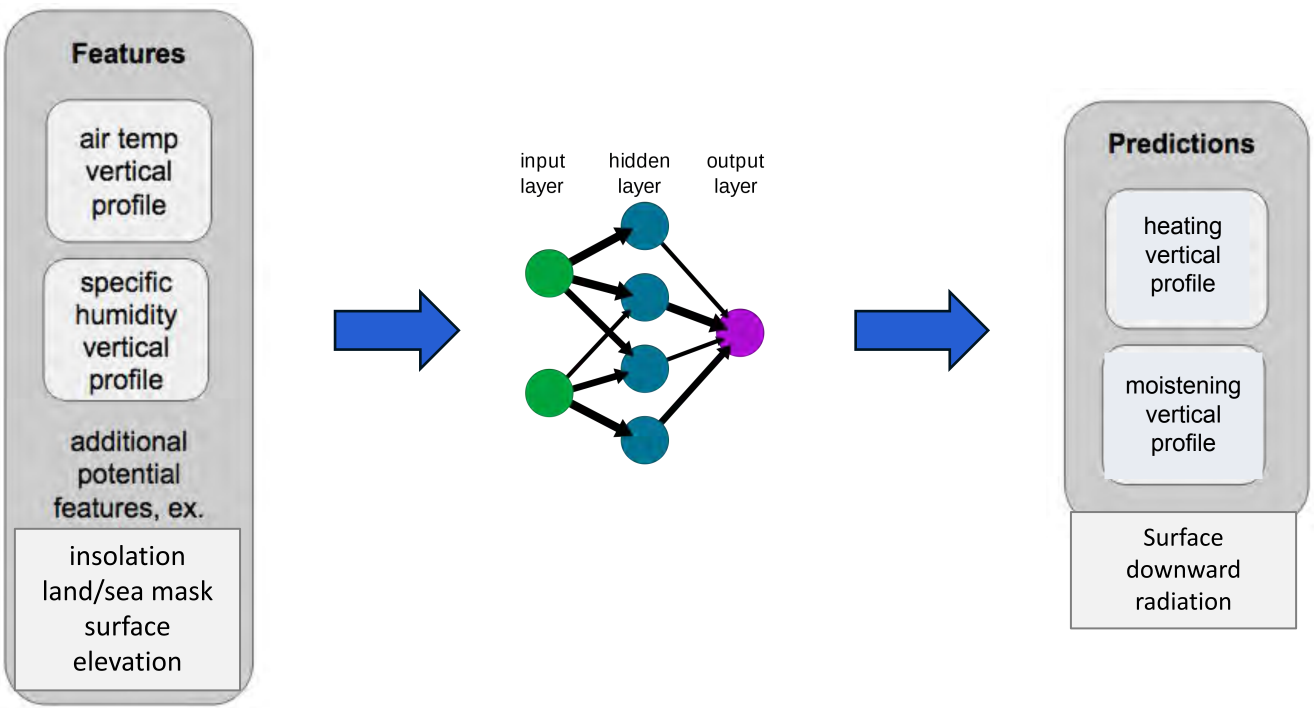


3 km grid gives a better rainfall simulation over land than 200 km:

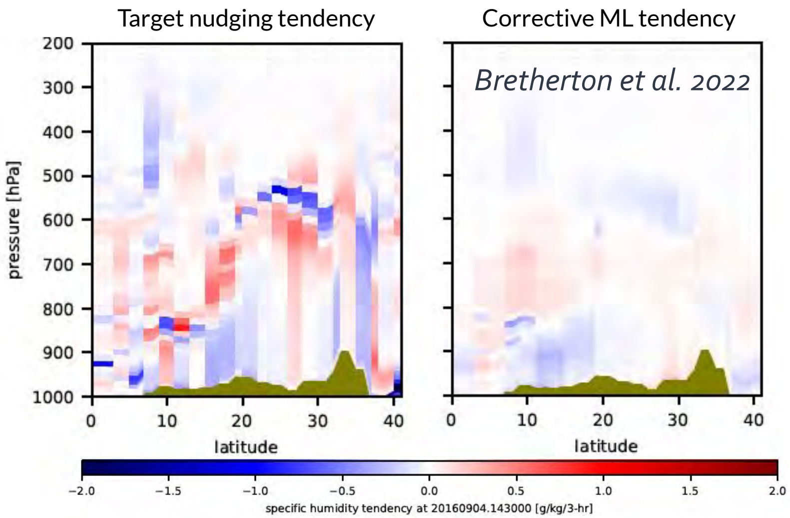
- Enabled by explicit simulation of cumulonimbus clouds & well-resolved mountains
- The 3 km model resolves variability that requires subgrid parameterization in GCMs

3 km model is expensive & imperfect but enables 1+ yr simulations in multiple climates

'Nudge to fine' ML methodology

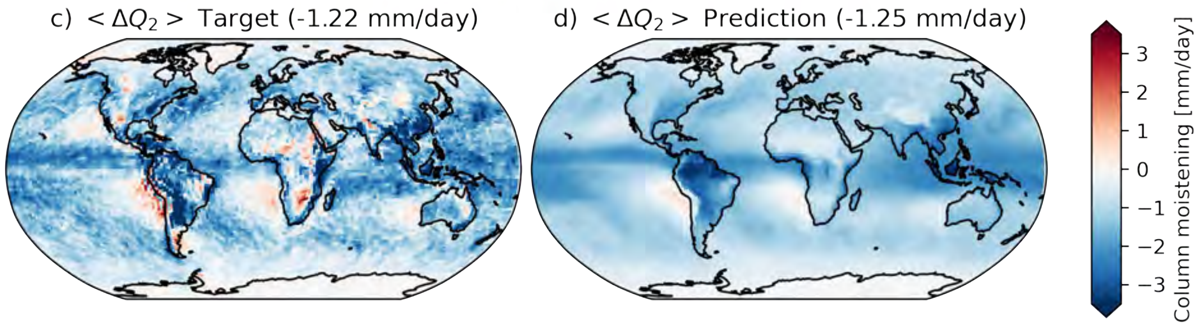


‘Nudge to fine’: ML offline evaluation



Nudging tendencies show systematic errors of coarse model vs. reference.

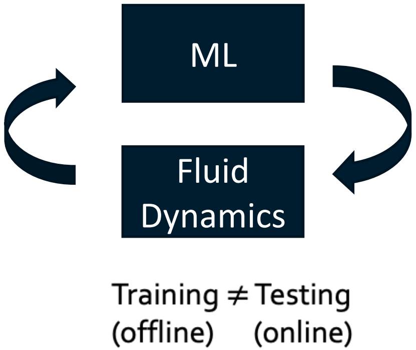
The ML schemes produce a smoothed, lower-amplitude, unbiased version of the noisy nudging tendencies

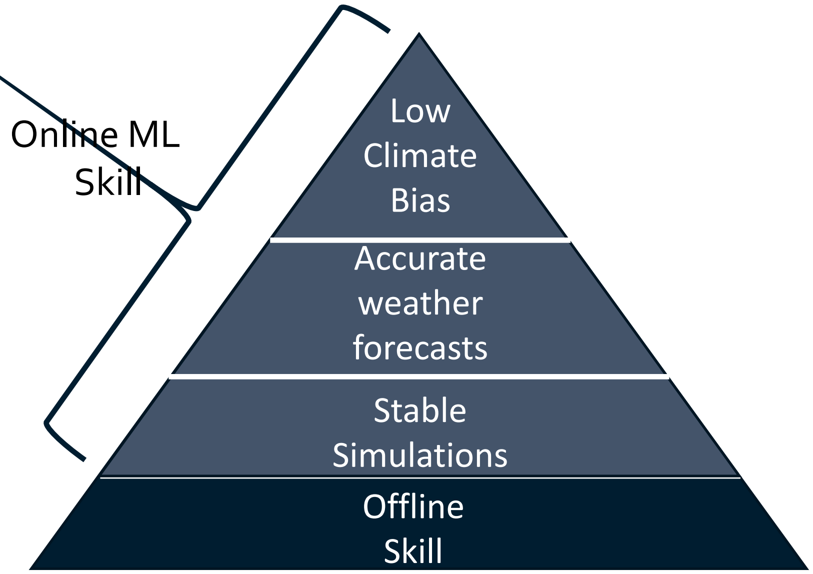


Watt-Meyer et al. 2021

Challenge of hybrid ML coupled to other components

Coupled to fluid dynamics and parameterized physics





Corrective ML results (200 km coarse, 3 km fine)

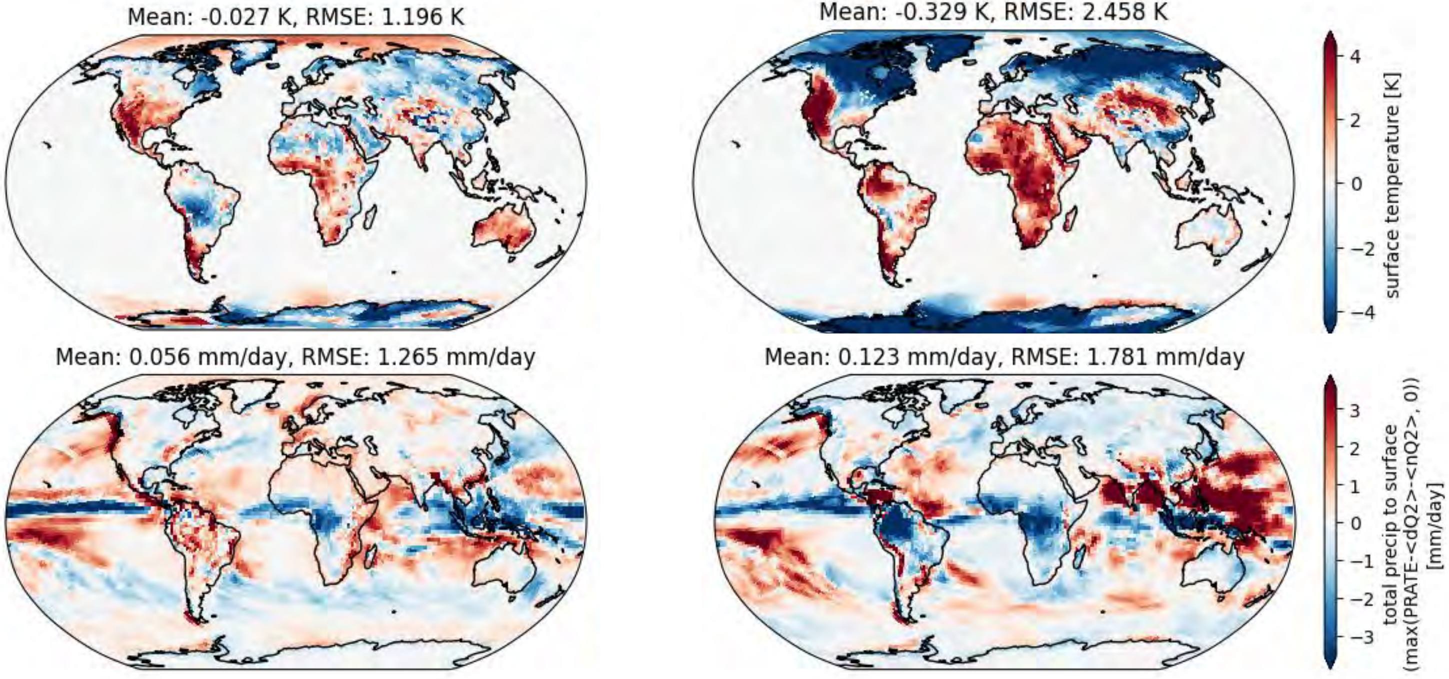
Presented to POS panel in 10/2022 by Oli Watt-Meyer:

- ML corrections trained using reanalysis reference (*Watt-Meyer et al. 2021*) add a day of forecast skill and improve mean surface precipitation patterns over land 20%
- ML corrections trained with 3 km GSRM reference improve land surface precipitation 20-30% (*Bretherton et al. 2022, Kwa et al. 2023*) and retain multiyear stability
- ML corrections to 200 km coarse model trained using 25 km AGCM reference across a range of climates specified using -4K, 0, 4K and 8K SST increments improve surface temperature and precip patterns by 10-30% in all climates (*Clark et al. 2022*)

Further climate bias reductions are ongoing

- With ML correction of u&v as well as T&q, annual-mean pattern biases of baseline are reduced 50% for surface temperature and 30% for surface precipitation.

ML-corrected bias **No-ML baseline bias**

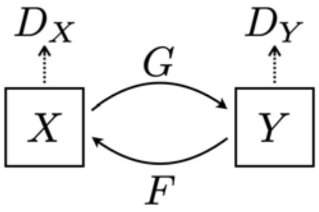


Further improvements attainable using out-of-sample detection (*Sanford et al. 2023*) and better coarsening algorithms

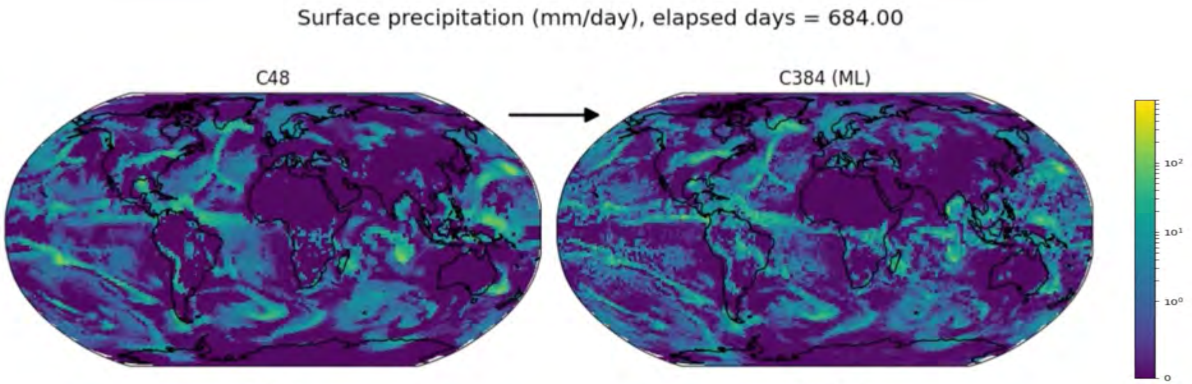
Can we improve on nudging-based corrective ML for climate?

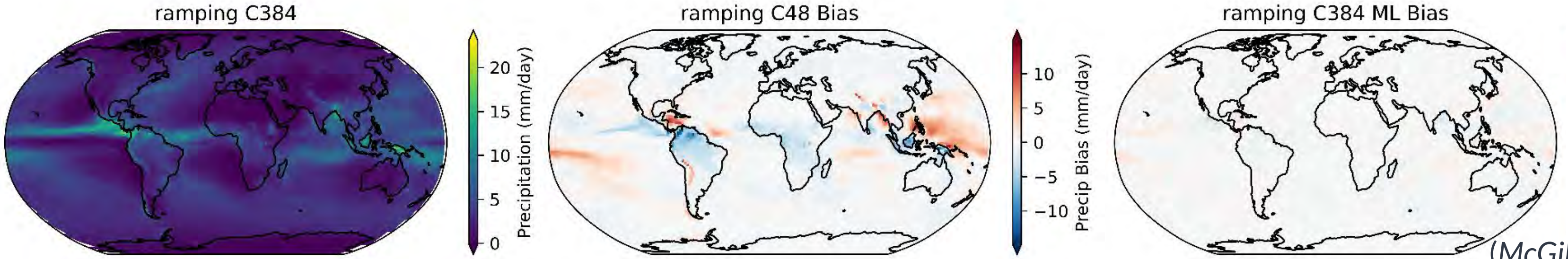
- Corrective ML trained on nudging tendencies improve forecast skill and land surface precipitation/temperature climatology of a coarse-grid global climate model by O(50%)
- It is physically interpretable and obeys mass, heat, and moisture conservation
- To make a really attractive emulator of a reference model, we must further reduce its climatological biases vs. reference target. This is challenging using our corrective ML
- We are thus investigating promising new approaches:
    - FME (e.g. FourCastNet, Pangu, GraphCast, ClimaX) - we have stable 10 year simulations
    - Hybrid reservoir computing (*Arcomano et al. 2022, 2023*)
    - CycleGAN post-processing of coarse model precipitation fields (*McGibbon et al. 2023*)

CycleGAN precipitation morphing (200 km->25 km)



Zhu et al. 2017





(McGibbon et al. 2023)

Mean annual precipitation bias almost perfectly removed across range of climates

Outlook

Hybrid:

- Can substantially improve climate relative to a reference
- Can be made fast
- Harder to efficiently train
- Easier to diagnose and enforce conservation laws

FME:

- Transformationally fast; better use of ML
- Skillful for weather
- Climate accuracy/stability in progress

ML (e.g. CycleGAN) is also a powerful tool for post-hoc bias correction

These tools may revolutionize applications-oriented climate modeling